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Residential mobility and unemployment in the UK

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ABSTRACT

The UK has suffered from persistent spatial differences in unemployment rates for many decades. A low responsiveness of internal migration to unemployment is often argued to be an important cause of this problem. This paper uses UK census data to investigate how unemployment affects residential mobility using small areas as potential destinations and origins and four decades of data. It finds that both in- and out-migration are affected by local unemployment - but also that there is a very high 'cost of distance', so most moves are very local. We complement the study with individual longitudinal data to analyse individual heterogeneities in mobility. We show that elasticities to local unemployment are different across people with different characteristics. For instance, people who are better educated are more sensitive, the same applies to homeowners. Ethnic minorities are on average less sensitive to local unemployment rates and tend to end up in higher unemployment areas when moving.

1. Introduction

Spatial inequalities in economic outcomes are very persistent in many countries (see Moretti, 2011, for a recent survey). The UK is no exception: Giovannini et al. (2019) argue it is the country with the highest level of regional inequality in Europe. These inequalities may also have political consequences: voters in 'left behind' areas seemed to play an important role in the Brexit vote (Fetzer, 2019).

In principle, mobility from depressed to booming areas should reduce these disparities, though this adjustment process inevitably takes time. There is evidence that migration does respond to differences in economic opportunity (for a thorough, though quite old, survey see Greenwood, 1997). The classic reference for the US is Blanchard and Katz (1992) who concluded that negative local labour demand shocks cause a short-run rise in the unemployment rate, but that migration causes unemployment rates to be equalized within 5–7 years, a relatively short time. The recent marked fall in residential mobility in the US (Molloy et al., 2011, 2014; Dao et al., 2017) has made people wonder whether this remains true. Amior and Manning (2018) argue that the migration response is slower than estimated by Blanchard and Katz (1992), that local demand shocks are highly persistent, and the interaction between these two factors induces high persistence in unemployment differentials. The conventional wisdom about Europe (e.g. Pissarides and McMaster, 1990; Decressin and Fatas, 1995; Overman, 2002; OECD 2005) is that adjustment is slower than in the US, though recently Amior and Manning (2019) find that the net migration response to unemployment in the UK is higher and more similar to the US than commonly believed. Although these studies provide convincing evidence that migration responds to economic opportunities, there is still surprisingly little evidence on the process in recent years[1] given the renewed concern about regional inequalities associated with the rise of political populism. This paper aims to contribute to our understanding of internal migration in three ways.

The first contribution is to consider very detailed information on location. Most existing studies of residential mobility use aggregate, region, state, or city level data. Sometimes, this is a choice dictated by data availability. But there is also a view that the ideal level of aggregation is local labour market level (what are called Travel to Work Areas – TTWAs - in the UK) and economic opportunity is best measured at this level of aggregation. However, there is evidence that labour markets are more local than TTWAs imply: most commutes are short and Manning and Petrongolo (2017) present evidence that vacancy filling rates are best explained by unemployment at neighbourhood level. If a TTWA is a single labour market, one would expect that all neighbourhoods within a TTWA should offer the same economic opportunities. As we show later, though, there is considerable variation in unemployment rates within TTWAs, even controlling for composition.

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[1] The survey of Greenwood (1997), seems to be the most recent.

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If labour markets are more local than TTWAs imply, it is important to take account of this both in estimating how residential mobility responds to unemployment and in designing policy. For example, very local interventions may be more effective the more local are labour markets. Amior and Manning (2019) show that the economic opportunities available to residents of an area can be summarized by a composition-adjusted employment or unemployment rate. Following their work, we will use unemployment as a measure of economic opportunities. To investigate the role of very local labour markets in modelling residential mobility, we estimate models including both a local (neighbourhood) level of unemployment as well as unemployment at the local labour market (TTWA) level. We find that both unemployment at the TTWA level and neighbourhood unemployment are important in explaining residential mobility. Even though residential moves tend to be local, often within the same TTWA, they tend to be from high to low unemployment neighbourhoods, and these very local moves play an important part in re-allocating labour from areas doing badly to those doing well.

The second contribution is to assess whether differences in economic opportunity across areas are more important in explaining in-migration or out-migration i.e. are people more likely to leave areas of high unemployment (an out-migration effect) or, given mobility, are they less likely to move to areas of high unemployment (an in-migration effect). This is relevant, as the elasticity to local unemployment may be different in these two sides of the problem. Although this is a question with a long pedigree (see the discussion in Greenwood, 1997) the literature on separate determinants of in- and out-migration is small. Coen-Pirani (2010) and Monras (2018) have argued, using aggregate US data, that in-migration is more sensitive to economic conditions than out-migration. Using aggregate UK data, Jackman and Savouri (1992) show that high unemployment raises out-migration and lowers in-migration to a similar extent. Our analysis show that both a high level of local unemployment and high level of TTWA unemployment increase out-migration on the one side and decrease in-migration on the other side. Both local and TTWA unemployment have an impact on mobility, both inflows and outflows.

The third contribution is to consider heterogeneity in the responsiveness of migration to unemployment. There is an extensive literature on how individual characteristics affect the probability of migration (again, see Greenwood, 1997, for a review, or Bound and Holzer, 2000 or Bütikofer and Peri, 2021), considering factors like age, education, family circumstances and housing tenure. There is a much smaller literature on how individual characteristics affect the responsiveness of migration to unemployment (or some other measure of economic opportunity).[2] This is important because the view that migration will tend to equalize economic opportunity is based on the idea that migration reduces competition for jobs in the areas left and increases it in the destination areas. Such a conclusion may not be justified if, for example, it was the best educated or the most ambitious who leave an area after a negative labour demand shock[3] – this would alter the skill mix in a way that might worsen labour market prospects for those left behind. In addition, studies of individuals that consider the impact of area economic opportunity on migration, tend to focus on out-migration because there is only one area an individual can leave at any time but a very large number of potential destinations. Those studies (e.g. Dahl, 2002; Kennan and Walker, 2011) that do consider a range of potential destinations typically have a relatively small number for computational issues. Our study provides evidence on how the impact of both destination and origin unemployment rates varies across individuals when a very large number of possible destinations are considered. We find that elasticity to unemployment at the destination level is more heterogeneous than at the origin level. People who are younger, married, homeowners, employed, and better educated tend to be more sensitive to unemployment at destination, while ethnic minorities tend to respond less. The reaction to TTWA unemployment is instead less heterogeneous. We will also provide two extensions to the individual model. The first analyses differences in the estimates with respect to reasons for moving, while the second re-estimates the models considering the choice to be a household choice.

The plan of the paper is as follows. In Section 2 we provide description of the Census data and some initial descriptive analysis on the mobility of people within the UK. Section 3 illustrates the empirical model we use for the Census data. Section 4 illustrates the analysis on the longitudinal data and its extensions. Section 5 concludes.

2. Census data

2.1. Description

We aim to estimate the impact of local economic conditions on migration between neighbourhoods. We use Census Area Statistics Wards (henceforth wards) as a definition of neighbourhoods. These are areas defined for statistical purposes during the 2001 census and have an average population of about 5000, partitioning Great Britain in 10,072 small areas.[4] We also use Travel to Work Areas (TTWA) as our measure of local labour markets. TTWAs are collections of wards produced by the Office for National Statistics[5] intended, as far as possible, to be self-contained labour markets.[6] There are on average 131 wards within a TTWA in Great Britain, but considerable variation: less than 10 wards in the less populated areas of the country to the maximum of 827 wards for the biggest TTWA (London).

The decennial Census for 1981–2011 (inclusive) provides aggregate counts of the number of people in England, Scotland and Wales who have moved between each pair of wards in the previous year.[7] This allows us to study mobility between a large number of origin and destination periods and over a quite long time. We also use area characteristics such as population, age structure, marriage rate, education, the share of immigrants, and housing tenure.[8] We use ward centroids to calculate the distance between wards and ward area to compute the av-

[2] Though some studies relate mobility to the current economic situation of the individual (Pissarides and Wadsworth, 1989; Hunt, 2006).

[3] On the interplay between skills and local labour market differences, a work on Germany by Dauth et al. (2018) shows, for instance, how the assortative matching of workers to firms can explain geographical wage differentials. Anelli et al. (2020) show that large emigration flows in Italy have a negative effect on entrepreneurship and this is mainly related to emigration of young and entrepreneurial individuals.

[4] This refers to England, Scotland, and Wales. Northern Ireland is not included in this study due to data homogeneity. Throughout the paper, the actual number of wards we have in our sample is 10071, as we aggregate the (adjacent) wards of Bishopsgate and of Walbrook due to continuity in the time series. In 2001 the CAS Ward construction was based on the Electoral Wards definition. The Electoral Wards are re-calculated at each Election, though, while we keep the definition of Wards fixed over time. Moreover, while the Electoral Wards are used for electoral purposes, they do not entail further differences in local governments or funding distribution, which are related to other, higher, geographical levels.

[5] See, for example, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/traveltoworkareaanalysisingreatbritain/2016.

[6] TTWAs are constructed so that at least 67% of those who live work there and 67% of those who work there also live there. The definition also sets minimum thresholds for the population (at least 25,000). Source: https://www.nomisweb.co.uk/articles/330.aspx. In this paper we use the 2001 TTWA definition, which we keep stable across years. There are 232 TTWAs in our dataset.

[7] Appendix A includes additional information on the harmonization of the area level datasets across censuses. The result is a dataset with over 100m observations times 4 years.

[8] Data is from the 1981-2011 Censuses of Population. Additional information on the variables included is in Appendix B.

erage distance within wards[9] which is important as they vary greatly in size.

Our focus is on estimating how economic conditions affect the mobility of people to and from the area. In many models of location choice, e.g. the classic Roback-Rosen model, labour supply is assumed to be inelastic and it is real wages that are the measure of economic opportunity. Kennan and Walker (2011) adopt a similar approach in using expected income. In contrast, we use the unemployment rate of residents as a summary measure of the level of their economic opportunity, though sometimes adjusted for the demographic characteristics of the area. This can be justified using the 'sufficient statistic' approach of Amior and Manning (2019) who show that, if there is any elasticity in the supply of labour to an area, the utility offered by living in an area can be written as a function of the utility obtained when non-employed in an area and the unemployment rate of residents in the area, which acts as a sufficient statistic for all the opportunities. This result does not assume that residents work in the area where they live – rather the unemployment rate of residents of an area summarizes the employment opportunities in all areas within commuting distance. The 'sufficient statistic' approach is very convenient because it means that we do not have to model commuting even though we are considering very small areas where most people work outside their ward of residence. Intuitively, if an area offers good commuting opportunities this should be reflected in a lower unemployment rate for residents. Using the unemployment rate as the measure of economic opportunity also has the advantage that it is readily available for very small areas: the UK census does not contain any information on income so real wages could not be used if it was the preferred measure.

One of the issues this paper explores is whether it is unemployment in the neighbourhood (ward) or local labour market (TTWA) influences the mobility patterns. To this end, we use two different measures of the unemployment rate: at TTWA and ward level.

The census data has the advantage that it is based on a 100% census of population so has a very large underlying sample, although this comes at the cost of not having any individual characteristics of the movers or stayers though we do have information on the demographic characteristics of areas that we use as controls. Table 1 shows descriptive statistics for the census variables.

Table 1
Descriptive statistics census data 1981–2011, ward-level dataset.

	Mean	SD
Movers% of contemporaneous population	9.478	5.276
Median Distance travelled by movers (km)°	4.61	–
Distance travelled by movers (km)°	35.07	79.81
Total Population	5623	4019
Unemployment CAS Ward level%	6.886	4.264
Unemployment CAS Ward level% - residualised	6.886	2.663
Unemployment TTWA level%	7.195	2.744
Unemployment TTWA level% - residualised	7.195	1.700
% of people below 16	19.853	3.881
% of people between 16 and 29	18.133	5.415
% of people between 30 and 44	20.807	3.384
% of people between 45 and 59	18.996	3.614
% of people between 60 and 64	5.693	1.615
% of people above 65	16.518	5.648
% of married	39.894	20.641
% of graduates	13.839	8.730
% of foreign born	6.535	7.767
% students (on population 16–64)	5.695	4.826
% house owners	66.614	17.197
% social housing	21.356	17.055
N	40,284	

Note: 1981–2011 Census of Population data (Source: Nomis) at the CAS Ward level. °The *Median Distance travelled by movers* and the *Distance travelled by movers* represent the median and the average (and standard deviation) of the distance between two CASWards that have a non-zero flow of movers in the year before the census. Both the measures are weighted by the number of people moving between the two areas. Residualised measures of unemployment are estimates from a model that accounts for log of total population, percentage of people with university degree, age distribution, percentage of married/couples, percentage of students, percentage of people born outside the UK, percentage of homeowners and of people living in social housing. For this table, residuals from these models are then added to the average unemployment level. TTWA residualised measure of unemployment aggregate residuals form the CAS Ward level to the TTWA level.

2.2. *Descriptive statistics on spatial inequalities and mobility*

2.2.1. *Persistent spatial inequalities*

To illustrate the long-run aspect of spatial inequalities in the UK, Panel A of Fig. 1 shows the high correlation (0.77) between unemployment rates at the ward level in the 1981 and 2011 censuses. Panel B shows that TTWA level unemployment also has high persistence (correlation 0.76). Some of these differences are driven by persistence in demographic characteristics. However, controlling for population, age, marital status, migrants, education, and housing tenure still leads to a high correlation (0.47 for ward level unemployment, and 0.45 for TTWA unemployment), as Fig. D1 in the Appendix shows. There is also a high variance of within-TTWA unemployment rates, both controlling and not controlling for demographic characteristics as Fig. D2 in the Appendix shows. The intra-TTWA variation is consistent with the view that there are considerable differences in economic opportunities across areas in the same TTWA, even after controlling for area characteristics, suggesting that TTWAs should not be thought of as completely homogeneous labour markets.

2.2.2. *Residential mobility rates*

On average 9.5% of people have moved in the year before the census, and the average distance moved is 35 km. Most of the internal migration occurs within TTWAs – about 8 percent of the population move between wards every year compared to approximately 2 percent who move between TTWAs.[10] Census data (see Fig. D3 in the Appendix) indicates a small increase in residential mobility over time, but it is hard to draw strong conclusions about trends from 4 observations 10 years apart: there may be, for example, cyclical factors at work.[11] This pattern of relatively stable residential mobility rates contrasts with the United States trends, where the fall in mobility rates has attracted a lot of attention (Molloy et al., 2011, 2014; Kaplan and Schulhofer-Wohl, 2017; Ganong and Shoang, 2017).

Most residential moves are over short distances, and the fraction of moves over a certain distance is remarkably stable over time. Fig. D5 in the Appendix shows the fraction in each census of moves of different distances: over 50% are less than 5 km with less than 10% being more than 200km.[12] This is unsurprising, local moves allow people to keep existing jobs and contacts with friends and family, while longer moves are less likely to assure that.

[9] The average distance between wards is calculated as $\frac{128\sqrt{area_i}}{45\pi^{1.5}}$ which is the average distance between two randomly drawn points in a circle with that area.

[10] One implication of these differences is that studying internal migration at a high level of geographical aggregation as many existing studies do, may miss most residential mobility.

[11] The ONS uses NHS Register Data as the best available data source for internal migration between census years: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/migrationwithintheuk/bulletins/internalmigrationbylocalauthoritiesinenglandandwales/yearendingjune2015. This is the fraction of the population changing the region of their NHS registration: this data is not available for smaller areas than regions. Figure D4 in the Appendix presents data on regional mobility from as well as the Census data: the NHS data shows a slightly higher proportion of movers with respect to the census data, but little change over time.

[12] Figure D6 in the Appendix shows the corresponding cumulative distribution of the share of movers by distance.

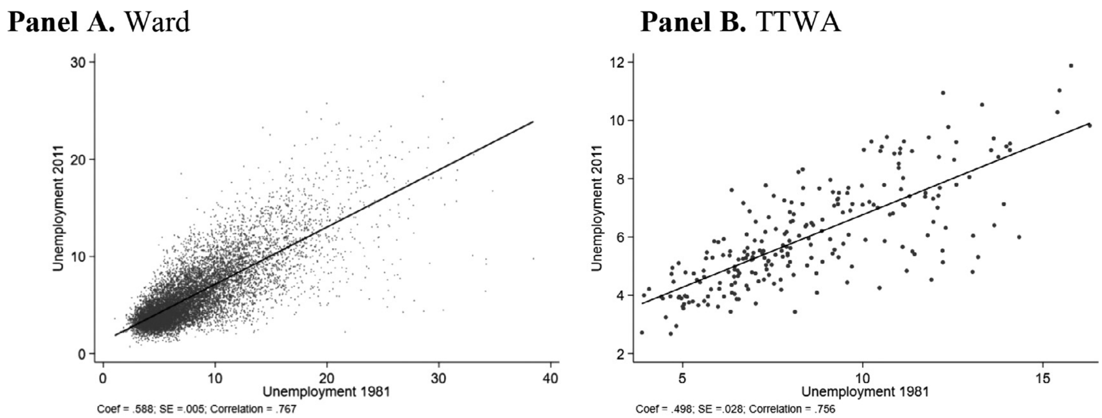

Fig. 1. Correlation in the unadjusted unemployment rate between 1981 and 2011.
Note: Authors' elaboration of 1981 and 2011 census data at the CAS Ward level and TTWA level, Source: Nomis. Coef refers to the estimated coefficient of a linear regression between the two variables, SE to the corresponding standard error. Linear interpolation is illustrated in both graphs.

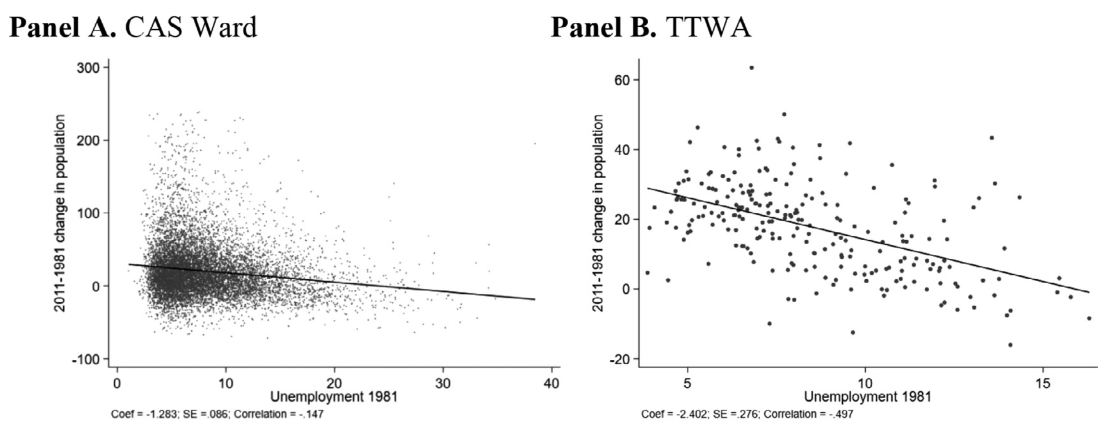

Fig. 2. The relationship between changes in population 1981–2011 and 1981 unemployment rates.
Note: Authors' elaboration of 1981 and 2011 census data at the CAS Ward level and TTWA level, Source: Nomis. Coef refers to the estimated coefficient of a linear regression between the two variables, SE to the corresponding standard error.

2.2.3. Is migration from high to low unemployment areas?

Migration from areas of high to low unemployment is one economic mechanism that could reduce spatial inequalities in labour market opportunity. Fig. 2, Panel A shows that wards with high unemployment in 1981 have lower average population growth in the period 1981–2011 (correlation of −0.15). At the TTWA level the correlation between population changes and initial unemployment levels is stronger (−0.50, Panel B). However, this migration does not seem high enough to equalize economic opportunity across areas as Fig. 1 shows very persistent differences in unemployment rates.[13] Aggregate population growth may be due to different factors (e.g. foreign immigration) so are not necessarily informative about mobility rates.

A more formal way to provide descriptive evidence on the extent to which individuals move from areas of high to low unemployment is the following. Denote by M_{abt} the number of movers from area a to area b at time t, u_{at} the unemployment rate in area a at time t. Define the average change in the unemployment rate experienced by movers as:

$$\frac{\sum M_{abt}\left(u_{bt}-u_{at}\right)}{\sum M_{abt}} \tag{1}$$

This will be a negative number if, on average, movers go from high to low unemployment areas. Eq. (1) can be interpreted as a simple measure of the strength of the propensity to move towards areas of greater opportunity. It is not a measure of whether the individual mover will have a higher probability of employment after moving nor a measure of how much mobility will reduce unemployment differentials between areas (though this might be expected if mobility reduces population in depressed areas and it increases population in areas that are thriving).

Table 2 shows the numerical equivalent of Eq. (1) in the Census data. The first row and first column shows that, on average, movers move towards wards that have an unemployment rate 0.135 percentage points below their current one i.e. the direction of travel is, on average from high to low unemployment areas. When using unemployment rates adjusted for differences in area composition (first row, column 2) the gap is smaller (−0.066) but still negative.

Appendix C shows how this overall direction of travel can be decomposed into several components. First, there are those who remain within the same TTWA – panel (b) of Table 2 – who represent 72.5% of movers. For them we can compute the average change in the unemployment rate of their origin and destination ward; the average value of the change is −0.149 on the unadjusted unemployment rate and −0.050 on the adjusted (columns 1 and 2, respectively). The overall contribution of within TTWA moves is then the product of the probability times the change which is reported at the bottom of panel (b) of Table 2.

Second there are the movers who change TTWA – panel (c) - this is 27.5% of movers as shown in row (c1). For them, the change in the unemployment rate between origin and destination can be split into a part due to the difference in unemployment rate in the origin and destination TTWAs (row (c2)) and a part which is the result of them moving

[13] Amior and Manning (2019) argue this is because demand shocks at local level are very persistent.

Table 2
Decomposition of average unemployment difference between wards of origin and wards of destination.

	(1) Unemployment Ward level%		(2) Unemployment Ward level% - adjusted	
(a) Average unemployment difference		−0.135		−0.066
(b) Within TTWA				
(b1) Percentage of total moves	*72.5%*		*72.5%*	
(b2) Within TTWA unemployment difference	−0.149		−0.050	
	(0.064)		(0.063)	
Contribution to the average (a)=*b*(1)*b(2)		−0.108		−0.036
(c) Between TTWA				
(c1)Percentage of total moves	*27.5%*		*27.5%*	
(c2) Between TTWA (net) unemployment difference	−0.183		−0.056	
	(0.126)		(0.072)	
(c3) Deviation from the mean unemployment difference	0.084		−0.051	
	(0.190)		(0.037)	
Contribution to the average (a)=*c*(1)*[c(2)+(c3)]		−0.027		−0.030

Note: 1981–2011 Census of Population data (Source: Nomis). Adjusted unemployment (column 2) is derived as the residuals from a model that account for control for population, age structure, marriage status, education, country of birth, students, house tenure. Within TTWA corresponds to $\frac{\sum_{ttwa(a)=ttwa(b)} M_{abt}(u_{bt}-u_{at})}{\sum_{ttwa(a)=ttwa(b)} M_{abt}}$ from equation (C.3) in the Appendix; Between TTWA: Between TTWA (net) is $\frac{\sum_{ttwa(a)\neq ttwa(b)} M_{abt}(u_{bt}^{ttwa}-u_{at}^{ttwa})}{\sum_{ttwa(a)\neq ttwa(b)} M_{abt}}$ from equation (C.2) Between TTWA: Deviation from the mean is $\frac{\sum_{ttwa(a)\neq ttwa(b)} M_{abt}[(u_{bt}-u_{bt}{}^{ttwa})-(u_{at}-u_{at}{}^{ttwa})]}{\sum_{ttwa(a)\neq ttwa(b)} M_{abt}}$, from equation (C.3);. Standard deviation in parenthesis.

between wards that do relatively better or worse within those TTWAs (row (c3)). Row (c2) shows there is a tendency to move from high to low unemployment TTWAs but row (c3) shows that for the unadjusted unemployment rates there is a tendency to move from a ward that had a relatively low unemployment rate in the origin TTWA to a ward with a relatively high unemployment rate in the destination TTWA. The overall contribution of between TTWA moves is then the sum of rows (c2) and (c3) multiplied by the proportion of people who change TTWA (27.5%) which is given at the bottom of panel (c). The sum of the terms at the bottom of panels (b) and (c) add up to the number in row (a). Table 2 shows that intra-TTWA moves explain the majority of the movement of people from high to low unemployment areas; for the unadjusted unemployment rates intra-TTWA moves account for 80%; for adjusted unemployment rates it is approximately 55%. This is partly because these moves are more frequent but also because the direction of movement is just as strong as for between TTWA moves.

The evidence presented so far has been descriptive and has not controlled for other relevant factors. We now turn to more formal empirical models.

3. The empirical model

To model the flows of people between wards we use a gravity-type model. Due to the large number of zeroes, we use a Poisson regression model. In this model, the number of movers from ward a to ward b at time t, M_{abt}, follows a Poisson distribution with mean given by:

$$E\left(M_{abt}|regressors\right) = \exp\left(\theta_{ab} + \beta_a x_{at} + \beta_b x_{bt}\right) \tag{2}$$

θ_{ab}, are time-invariant origin-destination fixed effects, which measure the attractiveness of area b to those currently living in a, x_{at} are time-varying origin characteristics, and x_{bt} are time-varying destination characteristics (our particular interest will be on the unemployment rate but we often have other controls). The origin-destination fixed effects encompass both time-invariant origin and destination characteristics and time-invariant characteristics of the origin-destination pair such as the distance between them.

The impact of origin and destination characteristics will reflect the factors making the ward an attractive or unattractive place to leave but also the origin characteristics will also reflect the fact that some types of people are more mobile than others. Because the role played by origin and destination characteristics is rather different, there is no reason to expect that their coefficients will necessarily be the same in (2).

In analysing mobility decisions there is also the issue of whether it is the current level of economic opportunity alone that matters or whether expectations about future opportunity also play a role (as perhaps should be the case, given that residential mobility is costly). The current framework can incorporate dynamic models if the payoffs from moving to an area are interpreted as value functions rather than flow utilities (see, for example, Arcidiacono and Elickson, 2011) though how one does this in practice is more difficult. Kennan and Walker (2011) estimate a dynamic discrete choice model of migration, but this is computationally very demanding (even though they have many fewer possible destinations than us) and involves imposing rather than estimating a discount factor assuming rather than estimating the extent to which individuals are forward-looking in making their decisions.

We prefer to simply condition on current measures of economic opportunity. Gallin (2008) showed that current conditions can be a sufficient statistic for future conditions if those conditions follow a Markov process. The coefficient on current unemployment should then be interpreted as a mixture of the impact of current and expected future conditions and the dynamic process followed by those conditions. But, without imposing strong further restrictions e.g. on discount factors, there is little prospect of making progress in disentangling the impact of current and expected future conditions.

Table 3 shows the results for the model represented by Eq. (2). In columns 1–3 we present results for a model that includes time fixed effects only, as a reference. The first column includes unemployment at the destination and origin ward level (neighbourhoods). The second column includes unemployment controls measured at the TTWA level (local labour market). The third column includes both ward and TTWA unemployment levels. In this last specification – as well as in all other specifications where both measures are included - we re-define ward unemployment as the difference between unemployment at the ward and TTWA level. The coefficient on TTWA unemployment can then be interpreted as the impact for an average ward in the TTWA. In all specifications the relation between unemployment and flows is positive, implying that, while people are more likely to leave high unemployment areas, they are also more likely to move to high unemployment areas. However, this conclusion may obviously be caused by the omission of variables correlated with both unemployment and mobility.

In columns 4–6 we control for any fixed characteristics by adding origin-destination pair fixed effects. This is a demanding specification, identifying the impact of unemployment through the relationship be-

Table 3
Residential mobility and economic conditions. Dependent variable: number of residents who moved between two wards in the year before the census.

	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson	(5) Poisson	(6) Poisson	(7) Poisson	(8) Poisson	(9) Poisson
Unemployment% D Ward	0.033***		0.024***	−0.019***		−0.025***	−0.006***		−0.003***
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)
Unemployment% O Ward	0.037***		0.034***	0.001		−0.008***	0.007***		0.008***
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)
Unemployment% D TTWA		0.065***	0.060***		−0.017***	−0.018***		−0.021***	−0.022***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Unemployment% O TTWA		0.043***	0.040***		0.030***	0.031***		0.013***	0.014***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Obs	14,068,896			14,068,896			14,068,896		
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination*Origin Ward FEs				Yes	Yes	Yes	Yes	Yes	Yes
Time varying Ward controls							Yes	Yes	Yes

Note: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$ In parenthesis the standard errors account for clusters at the destination-origin level. Data from the Censuses of Population from 1981 until 2011. D Ward refers to variables at the Destination CAS Ward level, O Ward refers to variables at the Origin CAS Ward level, D TTWA refers to variables at the Destination Travel to Work Area level, O TTWA refers to variables at the Origin Travel to Work Area level. When both TTWA and Ward unemployment levels are included, the Ward unemployment is calculated as a difference between Ward and TTWA level. Control variables coefficients for Columns 7–9 are shown in Table D1 in the Appendix. Population at origin is included as an exposure parameter in Columns 7–9. Control variables included in columns 7–9 are the logarithm of the population at destination, percentage of people with university degree, age distribution, percentage of married/couples, percentage of students, percentage of people born outside the UK, percentage of homeowners and of people living in social housing, at both ward of origin and ward of destination level.

tween changes in residential mobility across areas and changes in unemployment. When included separately (columns 4 and 5) origin ward and TTWA unemployment rate tends to have a positive impact on flows, though not always significant, while ward and TTWA unemployment at destination have a significant negative impact on inflows. When the TTWA and ward unemployment levels are jointly included (column 6) the picture is less clear as the origin ward differential unemployment shows a negative relation with mobility flows. The TTWA unemployment shows instead a positive coefficient at the outflow level and negative at the destination level.

In the regressions in columns 4–6, the only variable with both time-series and cross-section variation is the unemployment rate. There may be other time varying area characteristics that can play a role in flow dynamics. In columns 7–9 we include both origin and destination ward characteristics: age structure, percentage of people with university degree, percentage of foreign born, percentage of married couples, and percentage of home owners and in public housing.[14] We include population at origin as an exposure variable (so the dependent variable can be interpreted as a rate) and the log of population at destination as a control variable. The specifications in Columns 7–9 are our preferred ones as they consider pair fixed effects as well as time varying origin and destination characteristics.

When we include time varying characteristics, we find that unemployment is negatively related to inflows and positively related to outflows. The relationship with TTWA unemployment is stronger than with ward unemployment though all effects are significantly different from zero. TTWA unemployment has, in absolute value, a bigger impact on inflows than on outflows while forward unemployment it is the other way round.

Even though our preferred models are demanding specifications that consider both a broad set of origin and destination characteristics and a broad set of fixed effects, there may still be omitted time varying factors that bias our results although the direction of any bias is not clear. To correct for these potential endogeneities, we also estimate our models with a control function approach. As exogenous variation we use the time varying changes in the prevalence of two industrial sectors with large changes over the observation period: manufacturing and construction. The instrumental variables are the predicted shares in the said industries, constructed in a Bartik IV fashion

$$\hat{S}_{jat} = s_{jat_0} \frac{E_{jt} - E_{jt-1}}{E_{jt-1}}$$

where s_{jat0} is the share of workers in the sector j – construction or manufacturing - in area a at some initial time t_0, which in our case is 1971, E_{jt} is the national level of employment in sector j at time t. This allows to isolate the local economic shock deriving from the initial industrial composition of the area and national fluctuations in the industry. The variation being exploited is an interaction between area and time because we include area and time fixed effects. This means our estimates are not vulnerable to recent criticisms on the possible endogeneity of the initial shares used in the construction of the shift-share instrument in a single cross-section or, in a panel where time-varying initial shares are used (Borusyak et al., 2018; Jaeger et al., 2018; Adão et al., 2019; Goldsmith-Pinkham et al., 2020). As our models use time-invariant initial shares and control for ward-pair fixed effects, endogeneity of initial shares cannot be a concern. Our identification comes from the interaction between the initial shares which vary across areas but not over time and aggregate industry employment growth that varies over time but not across areas; we are assuming that changes in industrial structure affect residential mobility through an effect on economic opportunity as measured by the unemployment rate. The two shares are used as separate instrumental variables and constructed both at the ward level and at the TTWA level.

Table 4 shows the results for the control function specifications.[15] Results are similar to their non-control function counterparts. The main difference is that, in our preferred and most complete specification (column 9), ward unemployment rates are more relevant on the inflow side, while the role of ward unemployment at the outflow side is negligible. The role of unemployment at the TTWA level is greater when we use the control function approach, both on the inflow and on the outflow side, and almost symmetrical in magnitude.

Our main specification assumes it is only the current unemployment rate that influences migration decisions but there could be more complicated dynamics. Our ability to estimate these dynamics is limited by the 10 year difference between our observations but Table 5 presents some estimates where we include the 10-year change in the unemployment

[14] These variables are described in more detail in Appendix B. Coefficients on the control variables coefficients are displayed in Table D1 in the Appendix.

[15] First stages coefficients are displayed in Table D2 in the Appendix, while control variables coefficients are shown in Table D3 in the Appendix. We use a control function approach rather than a two stages least squares as we are in a non-linear setting.

Table 4
Residential mobility and economic conditions: control function specifications. Dependent variable: flow of residents between two wards in the year before the census, 1981–2011 census.

	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson	(5) Poisson	(6) Poisson	(7) Poisson	(8) Poisson	(9) Poisson
Unemployment% D Ward	0.116***		0.103***	0.085***		0.047***	−0.016**		−0.018***
	(0.002)		(0.002)	(0.006)		(0.007)	(0.006)		(0.006)
Unemployment% O Ward	0.085***		0.078***	0.086***		0.056***	−0.012*		−0.008
	(0.002)		(0.002)	(0.006)		(0.007)	(0.006)		(0.006)
Unemployment% D TTWA		0.152***	0.144***		0.020**	0.059***		−0.070***	−0.045***
		(0.003)	(0.003)		(0.008)	(0.009)		(0.011)	(0.011)
Unemployment% O TTWA		0.086***	0.086***		0.145***	0.146***		0.087***	0.049***
		(0.003)	(0.003)		(0.008)	(0.010)		(0.011)	(0.011)
Obs	14,067,840			14,067,840			14,067,840		
Year Fes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area pair Fes				Yes	Yes	Yes	Yes	Yes	Yes
Time varying ward controls							Yes	Yes	Yes
F-test excluded IV D Ward	102,796		67,448	17,325		13,117	13,830		15,177
F-test excluded IV O Ward	111,125		67,712	19,718		13,171	14,099		16,322
F-test excluded IV D TTWA		187,672	94,085		46,805	23,811		13,469	11,371
F-test excluded IV O TTWA		196,012	98,323		55,943	28,324		16,637	12,961

Note: *p<0.1, **p<0.05, ***p<0.01 In parenthesis the standard errors account for clusters at the destination-origin level. Data from the Censuses of Population from 1981 until 2011. D Ward refers to variables at the Destination CAS Ward level, O Ward refers to variables at the Origin CAS Ward level, D TTWA refers to variables at the Destination Travel to Work Area level, O TTWA refers to variables at the Origin Travel to Work Area level. When both TTWA and Ward unemployment levels are included, the Ward unemployment is calculated as a difference between Ward and TTWA level. Control variables coefficients for Columns 7–9 are shown in Table D3 in the Appendix. Population at origin is included as an exposure parameter in Columns 7–9. Control variables included are population at destination (in thousands), percentage of people with university degree, age distribution, percentage of married/couples, percentage of students, percentage of people born outside the UK, percentage of homeowners and of people living in social housing, at both ward of origin and ward of destination level.

Table 5
Residential mobility and economic conditions: Controlling for changes in unemployment. Dependent variable: flow of residents between two wards in the year before the census, 1981–2011 census.

	(1) Levels Only	(2) Levels + Differences	
		(a)	(b)
	Level of Unemployment	Level of Unemployment	Difference in Unemployment
Unemployment% D Ward	−0.003***	−0.008***	0.005***
	(0.001)	(0.001)	(0.001)
Unemployment% O Ward	0.008***	0.012***	−0.004***
	(0.001)	(0.001)	(0.001)
Unemployment% D TTWA	−0.022***	−0.026***	0.003***
	(0.001)	(0.001)	(0.001)
Unemployment% O TTWA	0.014***	0.009***	0.005***
	(0.001)	(0.001)	(0.001)
Obs.	14,068,896	14,068,515	
Year Fes	Yes	Yes	
Destination*Origin Fes	Yes	Yes	
Time varying Ward controls (Levels)	Yes	Yes	

Note: *p<0.1, **p<0.05, ***p<0.01 In parenthesis the standard errors account for clusters at the destination-origin level. Ward unemployment is calculated as a difference between Ward and TTWA level. Control variables included are the logarithm of the population, percentage of people with university degree, age distribution, percentage of married/couples, percentage of students, percentage of people born outside the UK, percentage of homeowners and of people living in social housing, at both ward of origin and ward of destination level.

rate in addition to the current level; this specification has the advantage that the coefficient on the level of unemployment can be interpreted as the long-run impact of unemployment when it is not changing. The first column shows the estimates from our preferred baseline specification for comparison – column (9) of Table 3 Column (2a) shows the coefficient on the level of unemployment when we also include the change in unemployment. And column (2b) the coefficient on the change in unemployment in that model. Comparing columns (1) and (2a) one can see that, with the exception of the impact of the origin TTWA unemployment rate, the estimates in the extended model are larger in absolute terms than those in the baseline model, implying bigger effects of unemployment. In contrast, the coefficients on the change in unemployment are, again with the exception of the origin TTWA unemployment rate, opposite in sign and of smaller magnitude than the coefficients on the level of unemployment in column (2a). This implies that current and lagged unemployment have the same direction of impact on residential mobility. For the origin TTWA unemployment rate the estimates suggest that people are more likely to leave areas with both high and rising unemployment rates. While there is some evidence for dynamics being important, the estimates in columns (1) and (2a) are generally quite similar.

Our preferred interpretation of the impact of unemployment is the sufficient statistic result of Amior and Manning (2018, 2019). Those papers show that variation in the unemployment rate can be thought of as measuring how far down a labour supply curve residents are so can be thought of as a one-dimensional summary measure of economic welfare. Shifts in the local demand curve will change the unemployment rate by moving the local economy up the supply curve. The estimated impact of unemployment on mobility can be interpreted as the causal impact but there could be many channels through which this impact

Table 6
Decadal Changes in Log Population and Unemployment.
Dependent variable: Log changes in population at the ward level.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Ward Unemployment%	−0.003***	−0.004***	−0.004***	−0.007***
	(0.0004)	(0.001)	(0.001)	(0.001)
TTWA Unemployment%	−0.009***	−0.005***	−0.011***	−0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Destination Ward Unemployment% – weighted by mobility flows			0.002*	0.008***
			(0.001)	(0.001)
Obs.	30,213	30,213	30,213	30,213
Year Fes	Yes	Yes	Yes	Yes
Time varying Ward controls		Yes		Yes

Note: *p<0.1, **p<0.05, ***p<0.01 In parenthesis the standard errors account for clusters at the destination-origin level. Ward unemployment is calculated as a difference between Ward and TTWA level. Control variables included are the logarithm of the population, percentage of people with university degree, age distribution, percentage of married/couples, percentage of students, percentage of people born outside the UK, percentage of homeowners and of people living in social housing.

works in addition to variation in economic opportunity e.g. it could be that higher unemployment is associated with more crime which makes areas less attractive.

How large is the response of residential mobility to unemployment? Consider a situation where unemployment increases by 1 percentage point in all wards in the TTWA so that the TTWA unemployment rate changes but not the ward rate relative to the TTWA average. If we use the estimates from column (9) of Table 4, outflows from the TTWA would increase by 4.9% and inflows from all other areas by 4.5%; the estimated effects would be somewhat smaller if we used the estimates from column (9) of Table 3.

What does this mean for changes in population? The following approximation to log population change is useful:

$$d \log POP = \frac{I}{POP} d \log I - \frac{O}{POP} d \log O \tag{3}$$

Where I is inflows and O outflows. If inflows and outflows are initially balanced and across TTWA boundaries are 2.5% annually, our estimates from Table 4 imply that a 1 percentage point increase in unemployment is predicted to lead to a fall in population of 2.5*(0.049+0.045)=0.235 percentage points a year. The estimates from Table 3 imply a smaller fall, −0.09 percentage points a year.

As a check on the plausibility of these estimates we related observed changes in population to unemployment. Specifically, we estimate a model with the change in the log of ward population between census years as the dependent variable and various measures of unemployment in the initial year as explanatory variables. The results are reported in Table 6. In the first two columns we include the lagged TTWA unemployment rate and the deviation of the ward unemployment rate from the TTWA average. The first column includes only year fixed effects while the second column also includes time-varying ward characteristics (we do not include ward fixed effects as the model is for the first-difference in log population). The results indicate that, when all controls are included, a 1 percentage point increase in TTWA unemployment translates into a 0.5 percentage points decrease in population growth in the following 10 years. This is smaller than the one-year changes in population multiplied over 10 years implied by the estimates of Table 3 and 4 but there are two reasons why this should be expected.

First, these specifications do not take account of the potential impact of unemployment in destination areas. Higher unemployment in the areas to which people tend to move from this area will increase population growth in this area. Because most moves are local and there is spatial correlation in unemployment rates, origin and destination area unemployment rates are likely to be positively correlated leading to a bias in the estimated impact of the own-area unemployment rate. To allow for this we construct a weighted average of unemployment rates in likely destination areas using as weights the average fraction of people who move to that area from this area. Results including this weighted destination unemployment rate variable are reported in columns 3 and 4. This has the expected positive coefficient and the inclusion of this variable also has the effect of increasing the magnitude of the coefficients on the own-area unemployment rate variables.

However, the predicted change in population from a 1 percentage point increase in the unemployment rate remains less than 10 times the one-year impact estimated from our mobility models. A second plausible explanation for this is that while unemployment rates are very persistent they do show some mean reversion. A regression of the unemployment rate on the unemployment rate 10 years previously gives a coefficient of about 0.55[16] implying a one-year persistence rate of 0.94=0.55ˆ0.1. This means that a 1ppt rise in the unemployment rate today would be expected to be associated with a 0.94ppt rise in a year's time, a 0.88ppt rise in a two years time etc. If we assume this level of persistence, the impact of having a one-percentage point higher unemployment rate today on annual flows would have to be multiplied by (1–0.55)/(1–0.55ˆ0.1)=7.75 to give the expected impact of 10 years taking account of the likely change in the unemployment rate. Using the estimates from Tables 3 and 4 this leads to a predicted 10-year impact of a rise 1ppt rise in the unemployment rate on log population of 0.7 and 1.8 log points, respectively, similar to what is found in Table 6. So our results about the impact of unemployment on the one-year mobility rate and 10-year population change are broadly consistent.

While the inclusion of origin-destination pair fixed effects controls for a wide range of possible confounding factors, their inclusion does not allow to identify the impact of distance on moves, which is something of independent interest. In Appendix E we model the fixed effects estimated from Eq. (2) presented in column 9 of Table 3 as a function of distance and origin and destination characteristics. A model using the log of distance performs best and we use this specification in the individual modelling below. It is worth noting that we obtain very similar results on the Census data if we replace the origin-destination pair fixed effects with separate origin and destination pair fixed effects and a measure of distance so that the inclusion of pair fixed effects does not seem to be critical.

In conclusion we find that both the neighbourhood (ward) and labour market (TTWA) unemployment rate matter for mobility, consistent with the view that labour markets are more local than implied by conventional definitions of labour markets. The unemployment rate negatively affects inflows and positively affects outflows, thus causing population to move away from areas of high unemployment and towards areas of lower unemployment. This means that people tend to

[16] This coefficient is obtained also controlling for the usual local area characteristics, when only unemployment is included this amounts to 0.78.

move from areas with high to low unemployment. Because most moves are over short distances, moves within labour markets are important in this process and will be missed if the analysis is at the level of the TTWA.

4. The analysis of individual longitudinal data

4.1. Data and framework

Although the Census flow data documents the residential moves for the entire population between small areas, the aggregate nature of the data does not allow us to say anything about who moves and whether the responsiveness of mobility to unemployment is different for different groups.

To investigate this, in the second part of the paper, we analyse an individual-level longitudinal dataset, the British Household Panel Study (BHPS) that ran from 1991 to 2008 and its successor from 2009, the Understanding Society, the UK Household Longitudinal Study (UKHLS). Together, these two surveys allow us to track a sample of individuals from 1991 to 2014. All individuals aged above 16 in sampled households take part in the interview and answer a broad variety of questions. The geocoded version[17] of BHPS/UKHLS allows us to identify moves at a local level as in the Census data used earlier. BHPS/UKHLS also have more qualitative information on residential mobility e.g. it asks about the reason for any move. Movers are approximately 6 percent of the BHPS/UKHLS sample. This accounts for 33,783 moves in total and 19,589 individual movers.

BHPS/UKHLS data sets are too small to compute statistics about unemployment and demographics within these small areas so we use census data for these variables. For this section we use small area information from the three census years that overlap with the BHPS/UKHLS survey period – 1991, 2001, and 2011 – and we linearly interpolate for intra-census years.[18] Fig. D7 in the Appendix illustrates mobility across wards and TTWAs using the BHPS/UKHLS survey data. As for the census, most of the mobility occurs within TTWAs. The level of the year-to-year mobility flows are similar to the census data (Fig. D3 in the Appendix) in 2001 though the trends since the 2000s are a bit different with falls in mobility in the BHPS/UKHLS data.[19]

We are particularly interested in the impact on mobility of the interaction of individual characteristics with local unemployment. If some groups of people are more responsive than others to unemployment, residential mobility will change the mix as well as the level of population. In choosing the individual characteristics we follow what has been found to be important in previous work on residential mobility in the UK, Hughes and McCormick (1981, 1985) find private renters are more mobile, Henley (1998) finds that negative housing equity deters migration. Following this, the individual characteristics that we analyse are gender, marriage status, number of kids, age, education achievements, and house tenure.

Table 7
BHPS/Understanding society data - descriptive statistics.

	(1) Movers	(2) Not movers
Women (%)	0.534	0.541
	(0.499)	(0.498)
Married (%)	0.336	0.553
	(0.472)	(0.497)
Ethnic minority (%)	0.093	0.104
	(0.291)	(0.305)
Age	34.492	47.485
	(15.326)	(18.162)
With Higher Education Degree (%)	0.298	0.260
	(0.457)	(0.439)
With Mid-level Education (%)	0.346	0.266
	(0.476)	(0.442)
Homeowners (%)	0.495	0.742
	(0.500)	(0.437)
Social housing (%)	0.163	0.177
	(0.370)	(0.381)
Observations	33,783	399,630
Number of individuals	19,589	73,705

Note: British Household Panel Survey and Understanding Society Panel data. Movers are defined as individuals who are ever observed in different lower super output area in subsequent waves. Movers' characteristics are measured in the observed year before the moving.

Descriptive statistics for these data sets are reported in Table 7. The table shows that, in our sample, movers tend to be slightly better educated than stayers, they tend to be younger, and less likely to own a house or be in social housing. They are less likely to be people of colour and less likely to be married.

4.2. Estimation

Our empirical method for the BHPS is different from that used for the Census analysis to reflect the difference in the nature of the data. For the BHPS/UKHLS data we take a two-step approach to estimation. We first estimate a model for the destination ward conditional on changing residence; we call this the destination decision. It can be thought of as a model of in-migration into wards. Then, we use these results to estimate a binary model for whether an individual moves at all – this is the out-migration decision. This two-step approach has both practical and conceptual advantages. We assume that the utility of individual i currently living in a conditional on moving to b (which includes the possibility of moving within the current ward) at time t can be written as:

$$V_{iabt} = \beta_1 dist_{ab} + \beta_2 q_{it} + \beta_3 x_{bt} + \beta_4 x_{bt} * q_{it} + \varepsilon_{iabt} \quad (4)$$

Where q_{it} are the characteristics of individual i at time t, x_{bt} are area and destination characteristics, and $dist_{ab}$ is the distance between a and b (modelled as the log distance between every pair of areas). The final term in the specification in (4) allows for an influence of individual and area characteristics but also the interaction between them. We assume that the error term has an extreme value distribution so that this specification leads to a multinomial logit model of the destination, conditional on moving. We will then also have a logit model for the decision to move at all. Hence, the model is a nested logit in which the upper nest is the decision to move, and the lower nest is the decision on destination. The conceptual advantage of this approach is that it allows the factors influencing in- and out-migration to potentially be different. The practical advantage is that, by focusing on movers in the first step, the sample size is greatly reduced, and we can still consider the full set of destination wards.

[17] University of Essex. Institute for Social and Economic Research. (2014). *British Household Panel Survey, Waves 1-18, 1991-2009: Special Licence Access, Lower Layer Super Output Areas and Scottish Data Zones*. [data collection]. *3rd Edition.* UK Data Service. SN: 6136, http://dx.doi.org/10.5255/UKDA-SN-6136-2. University of Essex. Institute for Social and Economic Research, NatCen Social Research, Kantar Public. (2016). *Understanding Society: Waves 1-6, 2009-2015: Special Licence Access, Census 2001 Lower Layer Super Output Areas*. [data collection]. *7th Edition.* UK Data Service. SN: 6670, http://dx.doi.org/10.5255/UKDA-SN-6670-7

[18] Using interpolation will induce some measurement error in the intra-censual years but if the true unemployment rate varies randomly about the trend this form of measurement error will not induce bias. The alternative is to use the claimant count, an administrative measure of those claiming unemployment insurance but this only gives us the numerator in the unemployment rate and was also subject to several big changes in the design of the system reducing comparability of the statistics over time.

[19] The biggest fall is when the survey changes from BHPS to UKHLS. Even though weights are used that are designed to be representative, it is possible that the observed change is from the change in survey.

Due to the data structure, in this part of the paper the identification strategy relies essentially on a set of time-varying controls, on individual-year fixed effects, and on destination fixed effects. Even if the set of fixed effects included is quite broad, we cannot exclude the existence of unobservable variables at the area-pair level that affect the results, therefore in some specifications we will also use a control function approach similar to what we used for the census models. Contrary to the Census analysis, we cannot include origin-destination pair fixed effects as we only have one observation for many pairs in the individual data.[20]

4.2.1. In-migration: the destination decision

As we have a very large number of different possible destinations, the most practical way to estimate the multinomial logit model is to use the multinomial-Poisson transformation (Baker, 1994). Each observation is an individual who moves in a particular year so the fixed effect that needs to be included in the Poisson model is an individual*year fixed effect. This means that the level effect of individual characteristics on the destination decision in (3) will be subsumed in the fixed effects so can be dropped from the estimated model. The same applies to the origin area characteristics (including unemployment). But the impact or destination area unemployment and its interaction with individual characteristics can be identified and this is the focus of our analysis. The estimated models also include time-invariant destination fixed effects.

Table D4 in the Appendix illustrates a first set of basic models where no interactions are included. As in the census analysis, both destination ward and TTWA unemployment have a negative impact on the probability of choosing a specific area, though results are not as robust as for the census analysis once we start including destination fixed effects and controls (columns 4–9). This is likely because the individual data is much better-suited to identifying the interaction of characteristics with unemployment than the main effect as we typically have only a few observations moving to each destination ward: the average number of movers in an observed origin-destination pair is 1.6 and for many pairs we have no observations at all. As for the census dataset, we also estimate the model using a control function approach to correct for the endogeneity of unemployment. Table D5 in the Appendix presents the results which are not significantly different from the non control function ones, though more imprecise.

Estimating the full model illustrated by Eq. (4), with all unemployment interactions with individual characteristics is demanding computationally because of the high dimension of the individual level matrix. To overcome this issue, we use the 'big data bootstrap' procedure suggested in Kleiner et al. (2012), implemented as follows. We randomly create different subsamples of the dataset destination wards in the UK. Following Kleiner et al. (2012), each subsample contains 4060 individual-time units, which is, approximately, N^{γ} with $\gamma = 0.8$ and N being the total number of units. For each individual-time unit i in each subsample I we construct the full matrix of location alternatives. This procedure mechanically excludes destinations where nobody or just one unit from the subsample moves to, as these areas do not affect the estimated coefficients given the fixed effects included in the model. In each of the subsamples we then estimate the models in Poisson form. Coefficients and bootstrapped standard errors are then derived as weighted averages of the estimates from each run of the estimated model. As a check, Table D6 in the Appendix replicates the estimates of one of the models from Table D4 using this bootstrapping procedure, obtaining similar results.

Table 8 illustrates the results for the model that includes unemployment interactions as illustrated in Eq. (4). As elsewhere in the paper, three models are estimated, one with ward unemployment only, one with TTWA-level unemployment, and one including both, as well as the corresponding interaction terms with individual characteristics.[21] All models include individual-time specific fixed effects, destination fixed effects, logarithm of distance, and destination area characteristics from the small area census data. There are a lot of coefficients in these regressions, but the following patterns emerge. First, heterogeneities in

Table 8
Models for the choice of destination for movers in BHPS and Understanding Society data with interactions of unemployment at destination with individual characteristics. Dependent variable: indicator for moving to a specific ward.

	(1) CAS	(2) TTWA	(3) CAS & TTWA
Ward unemployment:			
Unemployment (Une)	0.048		0.060**
	(0.027)		(0.028)
Une*Age (mean rescaled)	−0.001***		−0.001**
	(0.0004)		(0.001)
Une*dependant child dummy	0.047		0.048
	(0.033)		(0.036)
Une*Mid level education	−0.025*		−0.029**
	(0.014)		(0.015)
Une*Higher education	−0.083***		−0.089***
	(0.016)		(0.017)
Une*Kids (No.)	0.013**		0.014**
	(0.006)		(0.006)
Une*Married	−0.072***		−0.073***
	(0.014)		(0.016)
Une*Ethnic minority	0.129***		0.120***
	(0.019)		(0.021)
Une*Own house	−0.057***		−0.066***
	(0.013)		(0.014)
Une*Woman	−0.001		−0.002
	(0.011)		(0.012)
TTWA Unemployment:			
Unemployment (Une)		−0.022	−0.021
		(0.062)	(0.063)
Une*Age (mean rescaled)		−0.002*	−0.002
		(0.001)	(0.001)
Une*Dependent child dummy		0.067	0.049
		(0.098)	(0.098)
Une*Mid level education		−0.005	−0.006
		(0.034)	(0.034)
Une*Higher education		−0.042	−0.052
		(0.038)	(0.037)
Une*Kids (No.)		0.006	0.005
		(0.016)	(0.016)
Une*Married		−0.051	−0.059
		(0.033)	(0.033)
Une*Ethnic minority		0.203***	0.197***
		(0.063)	(0.065)
Une*Own house		0.001	−0.004
		(0.031)	(0.031)
Une*Woman		0.001	0.000
		(0.027)	(0.027)

Note: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$ In parenthesis the standard errors account for clusters at the destination-origin level. Ward refers to variables at the Destination CAS Ward level, D TTWA refers to variables at the Destination Travel to Work Area level. When both TTWA and Ward unemployment levels are included, the Ward unemployment is calculated as a difference between Ward and TTWA level. The logarithm of linear distance between ward centroids is included in all models. Controls at destination included are log of total population, percentage of people with university degree, age distribution, percentage of married/couples, percentage of students, percentage of people born outside the UK, percentage of homeowners and of people living in social housing at the ward of destination level. The models are estimated on random partitions of the sample and subsequently aggregated as illustrated in Section 4.

[20] As noted earlier, we obtain very similar results on the Census data if we replace the origin-destination pair fixed effects with separate origin and destination pair fixed effects and a measure of distance. This latter specification is analogous to the specification estimated on the BHPS/UKHLS data where the origin fixed effect is subsumed in the individual fixed effect.

[21] As for the census analysis, in models that include both TTWA and ward unemployment, ward unemployment is defined as the difference between ward and TTWA unemployment.

the response to destination area unemployment seem more important for ward level than TTWA level unemployment, where only the ethnic minorities interaction coefficient stands out as significant, suggesting that ethnic minorities are less sensitive to the level of unemployment. Younger people, the better educated, the married, homeowners, and the employed are more sensitive to the level of unemployment in the ward, and therefore tend to move less to high unemployment wards. Ethnic minorities are less sensitive to the ward unemployment rates and tend to be more likely to move to high unemployment wards. The inclusion of TTWA level unemployment and interactions (Column 3) does not alter much these results. In terms of our theoretical model (4) that underpins our empirical model one would expect individuals to be more sensitive to unemployment, the more important are labour market outcomes relative to the idiosyncratic component of utility. For example, the young may be more focused on labour market opportunities in deciding on where to live.

4.2.2. Out-migration: the moving decision

Economic conditions and local characteristics affect the probability of moving away as well as the probability of picking a particular area when moving. In this section we estimate the probability of moving away using the panel from BHPS and Understanding Society.

As we previously mentioned, our model is essentially a nested logit structure in which the upper nest is the binary decision to move or not and, conditional on moving, the lower nest is the decision about the area to move to. The decision about whether to move or not is assumed to be determined by the difference between the utility achievable from remaining in the present location, V_{aat} and the expected utility conditional on moving, denoted by I_{at} (what is often known as the inclusive value). Given the multinomial logit structure for the location decision of movers, the inclusive value can be written as:

$$I_{at} = \log \sum_i e^{V_{ait}} \tag{5}$$

We use a first-order Taylor series approximation to the inclusive value to write the returns to moving as:

$$I_{at} - V_{aat} \approx \frac{\sum_b e^{V_{ab0}}\left(V_{abt} - V_{aat}\right)}{\sum_b e^{V_{ab0}}} = \sum_b p_{ab0}\left(V_{abt} - V_{aat}\right) \tag{6}$$

where p_{ai0} is the probability of moving from a to b in some base year . Eq. (6) has a simple interpretation: the inclusive value can be written as a weighted average of the returns to moving to other areas where the weights are the probability of making that move.

We use weights based on the estimates in Table 8 to compute a weighted average of unemployment rates in surrounding areas and we then include in our main model the difference between the unemployment rate in the place where the individual is living and the weighted average of the unemployment rate of all the other areas. The probability of moving at time t is modelled as a logistic function of the individual characteristics and of the difference between one's own area and potential destinations' unemployment rate at time $t-1$.

Table D7 in the Appendix shows the results for some baseline models with different sets of fixed effects. Columns 1–3 include year fixed effects as well as area of origin controls and individual controls – in the table we report unemployment coefficients only for readability. In column (3) with both ward and TTWA unemployment rates included, the difference in ward level unemployment has a positive impact on the probability of moving away from the area (as predicted by the theory), while TTWA level unemployment has a negative impact. However, when we add individual fixed effects in columns (4)-(6) - our preferred specification – both ward and TTWA unemployment rates in the current area of residence relative to likely destination areas has a significant positive effect on the probability of moving away.

As for the probability of moving in a specific area, it may be that the impact of the difference in unemployment is heterogeneous across different people. In Table 9 we re-run our preferred specification, corresponding to columns 4–6 of Table D7, including interaction terms of the ward and TTWA difference in unemployment with individual characteristics. We find that people who own a house and ethnic minorities react more to ward level unemployment, while people with more kids react more to TTWA level unemployment. In opposition, people who are married are less sensitive to TTWA unemployment (Column 3).

Overall, outflow models display a lower degree of heterogeneity than the inflow models we estimated in the previous section.

4.3. Extensions

In the Online Appendix we consider two extensions to the model: investigating heterogeneity by reasons for moving (job related, home related, area related, family related, and education related) and models for the behaviour of households rather than individuals as 74.7% of the individual moves in our dataset are associated to the whole household moving. The results for these extensions are broadly in line with the individual-level models.

5. Conclusions

There is renewed interest in spatial inequality in economic opportunity because it seems to play an important role in the current politics of many countries. One of the factors that might be expected to reduce spatial inequality is mobility of people from areas of low to high opportunity. Although the question of how mobility responds to unemployment is an old question, there is not as much recent research on the topic as one might expect given its importance.

Compared to the existing literature a main contribution of the paper is to argue that labour markets are more local than generally assumed so that one misses a lot of the action if the analysis only focuses on conventional definitions of labour markets aggregation such as Commuting Zones or TTWAs. Unemployment rates are not equalized within these labour markets as would be expected if they were unified labour markets. And most residential moves are only short distances so one needs to consider the role of these moves in re-allocating labour from high to low unemployment areas.

This paper develops an empirical method that can handle a large number of areas and applies the method to investigate the impact of unemployment on residential mobility in the UK. We find that both the neighbourhood (ward) and labour market (TTWA) unemployment rate matter for mobility, consistent with the view that labour markets are more local than would be implied by the use of conventional definitions of labour markets. The unemployment rate negatively affects inflows and positively affects outflows, thus causing population to move away from areas of high unemployment and towards areas of lower unemployment. This means that people tend to move from areas with high to low unemployment. Because most moves are over short distances, moves within labour markets are important in this process and will be missed if the analysis is at the level of the TTWA. And if labour markets are more local than TTWAs (and the evidence supports this view), these short moves are an important economic adjustment mechanism.

The conclusion that local moves and local unemployment plays an important role in the adjustment process has potential policy implications. It suggests that very local interventions in areas of high unemployment may be effective in reducing spatial inequalities.

We have also investigated heterogeneity in both the costs of distance and the responsiveness to unemployment using individual longitudinal data. Our main conclusions are that there are heterogeneities in the reaction to local unemployment, to the distance between areas and to the ethnic composition of the area. This is true both for inflows and for outflows. One of the implications of this is that easier residential mobility (a policy often recommended to lessen spatial inequalities) is likely to affect some groups more than others, affecting the demographic mix of areas that may also have important impacts on economic opportunities. Investigating these impacts is left for future research.

Table 9
Models for whether an individual moves in the year: Interactions of unemployment with individual characteristics. BHPS and Understanding Society data. Logit model. Dependent variable: indicator for whether a person has moved in a year.

	(1) CAS Ward	(2) TTWA	(3) CAS Ward & TTWA
Ward unemployment:			
Unemployment (difference)	0.027**		0.025**
	(0.013)		(0.012)
Unemployment (difference)*Age (mean rescaled)	0.001*		0.001
	(0.0003)		(0.0003)
Unemployment (difference)*Dependent child dummy	0.015		0.018
	(0.038)		(0.036)
Unemployment (difference)*Mid level education	0.002		0.000
	(0.011)		(0.010)
Unemployment (difference)*Higher education	−0.004		−0.007
	(0.015)		(0.010)
Unemployment (difference)*Kids (No.)	0.008*		0.006
	(0.004)		(0.005)
Unemployment (difference)*Married	0.013		0.017*
	(0.011)		(0.009)
Unemployment (difference)*Ethnic minority	0.034**		0.035**
	(0.017)		(0.014)
Unemployment (difference)*Own house	0.027**		0.026***
	(0.011)		(0.009)
Unemployment (difference)*Woman	−0.001		−0.004
	(0.009)		(0.010)
TTWA Unemployment:			
Unemployment (difference)		0.046	0.088*
		(0.051)	(0.052)
Unemployment (difference)*Age (mean rescaled)		0.001	0.001
		(0.002)	(0.002)
Unemployment (difference)*Dependent child dummy		−0.108	−0.097
		(0.137)	(0.134)
Unemployment (difference)*Mid level education		0.045	0.051
		(0.042)	(0.043)
Unemployment (difference)*Higher education		0.093*	0.093*
		(0.056)	(0.051)
Unemployment (difference)*Kids (No.)		0.047**	0.047***
		(0.022)	(0.015)
Unemployment (difference)*Married		−0.073*	−0.065*
		(0.044)	(0.036)
Unemployment (difference)*Ethnic minority		−0.019	−0.041
		(0.121)	(0.102)
Unemployment (difference)*Own house		0.046	0.038
		(0.038)	(0.038)
Unemployment (difference)*Woman		−0.064*	−0.067
		(0.038)	(0.045)
N	122,808	122,808	122,808

Note: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$ In parenthesis the bootstrapped standard errors. Controls included are log of total population, percentage of people with university degree, age distribution, percentage of married/couples, percentage of students, percentage of people born outside the UK, percentage of homeowners and of people living in social housing at the ward of origin level.

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Supplementary materials

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