Residential mobility and unemployment in the UK

LSE Research Online URL for this paper: http://eprints.lse.ac.uk/103398/

Version: Published Version

Monograph:

Langella, Monica and Manning, Alan (2019) Residential mobility and unemployment in the UK. CEP Discussion Papers. Centre for Economic Performance, LSE, London, UK.

ISSN 2042-2695

CENTRE *for* ECONOMIC PERFORMANCE

CEP Discussion Paper No 1639

July 2019

Residential Mobility and Unemployment in the UK

Monica Langella
Alan Manning

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

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 very small areas as potential destinations and origins and four decades of data. It finds that both in- and out-migration are affected by unemployment, although the effect on in-migration appears to be stronger - but also that there is a very high 'cost of distance' so most moves are very local. Using individual longitudinal data we show that the young and the better educated have a lower cost of distance but that sensitivity to unemployment shows much less variability across groups.

Key words: residential mobility, regional inequality, unemployment
JEL Codes: Z1, J01, R10, J21

This paper was produced as part of the Centre's Communities Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We would like to thank the ESRC for funding the research under grant ES/N012259/1 Migration and the North South Divide. We thank participants to the Royal Economic Society 2019 conference, and to the CEP conference for useful insights.
Monica Langella, Centre for Economic Performance, London School of Economics. Alan Manning, London School of Economics and Centre for Economic Performance, London School of Economics.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

1. Introduction

Regional inequalities in economic outcomes seem remarkably persistent in many countries (see Moretti, 2011, for a recent survey). This has political as well as economic consequences. Voters in 'left behind' areas seemed to play an important role in the Brexit vote (Fetzer, 2018) and the election of Donald Trump.

One of the main forces that economists expect to equalize economic opportunity across areas is migration: individuals leaving depressed areas for booming areas. There is strong evidence that migration does respond to differences in economic opportunity (for a thorough, though early, 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. However, Amior and Manning (2018) argue that for the US the migration response over decades is slower than that estimated by Blanchard and Katz (1992) and that local demand shocks are highly persistent, causing very persistent differentials in unemployment rates. The US has also had a marked fall in residential mobility in recent years that has attracted attention (Molloy, Smith and Wozniak, 2011, 2014; Dao, Furceri, and Loungani, 2017).

Similar exercises for Europe (e.g. Pissarides and McMaster, 1990; Decressin and Fatas, 1995; Overman , 2002; OECD 2005) find slower adjustment processes than in the US though Amior and Manning (2019) argue that the net migration response to unemployment in the UK is higher and more similar to the US than commonly believed. Although these studies do provide convincing evidence that migration does respond to economic opportunities, there is still surprisingly little evidence on the process in recent years (the survey of Greenwood, 1997, seems to be the most recent) and considerable gaps in our knowledge. This paper aims to contribute to our understanding of internal migration in three main areas.

The first contribution of this paper is to consider very detailed information on location. Most existing studies use aggregate, region, state, or city level data with the assumption (often only implicit) that the area being studied is a single self-contained labour market. However, Manning and Petrongolo (2017) argue that labour markets are much more local, and the average length of commute is short. In this paper we use UK wards that have an average population of about 5000. This gives us more variation in unemployment but also requires adoption of a framework that recognizes the existence of multiple overlapping labour markets. We develop methods to handle the large number of areas in our analysis. Our strategy to isolate the impact of local unemployment will rely on an extensive set of fixed effects and on an instrumental variable strategy that relies on a Bartik-style shift-share instrument designed to capture local demand shocks.

The second contribution of the paper is to assess whether differences in economic opportunity across areas is a more important driver of in-migration or out-migration i.e. are people are 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). 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.

The third contribution of this paper 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), 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)[1]. 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[2] – 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

[1] Though some of the individual characteristics sometimes considered is the current economic situation of the individual (Pissarides and Wadsworth, 1989, for early evidence for the UK) and age (Hunt, 2006, for Germany).
[2] 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.

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.

The plan of the paper is as follows. In the next section we provide some background on regional inequalities and residential mobility in the UK. The third section then provides our general framework for modelling both in- and out-migration. The fourth section describes how we apply this framework to aggregated Census data and presents our estimates for that data. The fifth section discuss the longitudinal data results. The sixth section concludes.

2. Background

In this paper we focus on the UK. The UK has long-standing spatial inequalities, often summarized as the "North-South" divide. Figure 1 shows the high correlation (0.77) between unemployment rates at the ward level[3] in the 1981 and 2011 censuses. Some of these differences are driven by persistence in demographic characteristics but controlling for age, marital status, migrants, and education still leads to a high correlation (0.41), as Figure 2 shows.

Migration from areas of high to low unemployment is one economic mechanism that might be expected to reduce spatial inequalities in labour market opportunity. There is some evidence that this has some role in the UK. Figure 3 shows that wards with high unemployment in 1981 have lower average population growth in the period 1981-2011 (correlation of -0.18). But the migration rate does not seem high enough to equalize economic opportunity across areas in the face of demand shocks at local level that are very persistent (Amior and Manning, 2019).

In the United States, a fall in mobility rates has attracted a lot of attention (Molloy et al., 2011, 2014; Kaplan and Schulhofer-Wohl, 2017; Ganong and Shoang, 2017). The UK historically has a lower level of mobility though it does not have a clear trend. Figure 4 presents the share of movers across wards (Panel A) with the share of movers across regions (Panel B), calculated using the Census data we use later in the paper. Most the internal migration occurs within regions – about 8 percent of the population move between wards every year compare to less than 2 percent who move between regions[4]. Census data seems to indicate an increase in

[3] Wards are small areas that, on average, account for 5,000 people. Throughout this paper we will use the Office for National Statistics CAS Ward definition of 2003. Further detail on the harmonisation of area level measures are provided in the Appendix.
[4] 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.

residential mobility over time but it is hard to draw strong conclusions from data that is 10 years apart: there may, for example, be cyclical as well as trend factors at work. For this reason, Figure 5 presents data on regional mobility from NHS Register Data[5], this shows a slightly higher proportion of movers with respect to the census data, and a quite stable pattern over time. Figure 6 shows data from the BHPS and Understanding Society surveys that we use in the second part of our analysis. As for the census data we compare the across wards annual mobility and the across region mobility. Levels of mobility are on average similar to the one recorded by census data, although the trend are a bit different with respect to what we see from census data, as here there is a clear downward trend in mobility. Differences between census and survey data can as well be ascribed to the different nature of the two datasets.

3. The model

We use a discrete choice framework as the underlying model. We assume that the residential location decision can be partitioned into two steps:

- The decision about whether to move residential location or not (the out-migration decision)
- Conditional on the decision to move, the decision about where to move to (the in-migration decision)

We therefore use a hierarchical structure in which in the upper nest contains the decision whether to move or not and in the bottom nest the choice is where to locate, conditional on moving. This allows to consider the in-migration and out-migration decisions separately. As it is standard for this type of models, the analysis starts from the second layer of the choice: where to move to, conditional on moving.

The In-Migration Decision

Suppose that there are A areas, denoted by a, a=1,..,A and individuals can potentially live in any of them. Assume the utility available to an individual previously living in a but moving to b at time t is given by:

[5] This is the fraction of the population changing the region of their NHS registration and is used by the ONS as the best available data source for internal migration between census years: see, for example, https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/migrationwithintheuk/bulletins/internalmigrationbylocalauthoritiesinenglandandwales/yearendingjune2015

$$U_{abt} = V_{abt} + \varepsilon_{abt} \tag{1}$$

Where V_{abt} is a measure of how attractive it is to live in b for an individual living in a (we will refer to V_{abt} as average utility). In addition we assume that ε_{abt} is an idiosyncratic utility shifter with an extreme value distribution which, as is well-known, leads to a logit specification for the probability of moving to *b* at time t given that one previously lived in *a*, p_{abt}:

$$p_{abt} = \frac{e^{V_{abt}}}{\sum_i e^{V_{ait}}} \tag{2}$$

The Out-Migration Decision

The decision about whether to move or not will be influenced by the utility achievable from remaining in the present location and the location decision that would be made if the individual did move and the utility available from that decision. A general form of writing this decision would be that the probability of leaving the current location is a function of the mean utility available in this and every other possible location (i.e. the value of the mean utilities V_{abt} in every area *b* is a potential regressor). In our application with more than 10000 possible locations, this approach is infeasible. Rather we define I_{at} as the expected utility conditional on moving, 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:

$$I_{at} = \log \sum_i e^{V_{ait}} \tag{3}$$

This can be estimated from our model of in-migration up to a constant – this is discussed in more detail later. We then assume that the fraction of people who leave their current residence, m_{at}, is a function of the difference in utility between remaining in the residence and the inclusive value. We assume a logit form for this so that we have:

$$m_{at} = \frac{e^{\beta_m\left[V_{at}^s - I_{at}\right]}}{1 + e^{\beta_m\left[V_{at}^s - I_{at}\right]}} \tag{4}$$

Where V_{at}^s is the utility from remaining in the current residence. We allow for this to be potentially different from V_{aat}, the utility from moving but remaining within the same ward (as

16.3% of movers do) because, for example, of mobility costs. 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.

4. Analysis of Census Data

a. The Data

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 – wards have an average population of about 5000[6]. The data is derived from the census question about place of usual residence a year ago combined with information on current residence. The definition of wards have changed over time but we construct a uniform census dataset based on the 2001 Census Area Statistic Wards, of which there are 10072[7]. For other years we convert to 2001 wards using postcode headcounts (details in Appendix B). Our starting point for the data set construction is then the population flows between the full matrix of ward pairs – over 100m observations times 4 years[8]. We merge this data set with area level characteristics from the census[9] such as population, age structure, marriage rate, education level, country of birth structure, and the unemployment rate as a measure of employment opportunity for residents of an area[10]. We also use the ward centroids to calculate the distance between, and average distance within[11], wards. Table 1 shows descriptive statistics for the census variables. On average 9.5% of people have moved in the past year, and the average distance of 35km[12]. This average reflects the fact that a high proportion of residential moves are local. Figure 7 plots the cumulative distribution of the share of residential moves for the 4 census years that are within a certain distance – the median distance moved is 4.6km[13].

---

[6] Source UK Data Service, Census Support, Flow Data. https://census.ukdataservice.ac.uk/get-data/flow-data
[7] 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 together the (adjacent) wards of Bishopsgate and of Waldbrook due to continuity in the time series.
[8] The dataset also contain within wards moves.
[9] 1981-2011 Censuses of Population, Source: Nomis.
[10] Source UK 1981-2011 Census data, Nomis.
[11] Within wards distance is calculated as the average distance between two points in the centroid $\frac{128\sqrt{area_i}}{45\pi^{1.5}}$
[12] This refers to the average distance between two wards that have a non-zero flow of movers in the year before the census, weighted by the number of movers.
[13] Weighted by the number of people moving between two areas.

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 having no individual characteristics. In the second half of the paper we use individual longitudinal data to investigate heterogeneity.

We now describe how we apply the model of the previous section to the census data.

b. Estimation of the in-migration decision

For the census data, we assume that V_{abt} in (1) can be written as:

$$V_{abt} = d_{ab} + W_{bt} \tag{5}$$

i.e. consists of a time-invariant term, d_{ab}, which measures the attractiveness of area b to those currently living in a and a time-varying destination term, W_{bt}, which measures the attractiveness of living in area b at time t. W_{bt} is assumed to be the same irrespective of the area a person moved from. The fact that people are more likely to move short distances is captured in the term d_{ab} which will be modelled as a function of distance. The time-varying term - W_{bt} – in our model is influenced by the amenities and employment opportunities offered by a destination area – and regarding the in-migration decision it is natural to assume that does not depend on the origin area.

Using (5) in (2) leads to the multinomial logit structure:

$$p_{abt} = \frac{e^{d_{ab}} e^{W_{bt}}}{\sum_i e^{d_{ai}} e^{W_{it}}} \tag{6}$$

In our application there are approximately 10,000 neighbourhoods representing possible destinations so that estimating a multinomial logit model directly is not computationally possible. Exploiting the multinomial-Poisson transformation (Aitkin and Francis, 1992, Baker, 1994, Guimaraes, 2004, among others) would similarly be problematic in this context, at it requires to estimate the model on the full area-pairs matrix as a Poisson with origin, destination, and time fixed effects. This approach is, as one might expect, highly computationally demanding and it would limit greatly the feasibility of robustness checks.

So in what follows we will estimate the models using a different approach. One can only identify the origin-destination fixed effects and destination-time fixed effects up to some normalizations - for example, the additional of a constant to W_{bt} or d_{ab}. To clarify what can be identified define:

$$D_{ab} = \frac{e^{d_{ab}+W_{b1}}}{\sum_i e^{d_{ai}+W_{i1}}} \tag{7}$$

And:

$$Z_{bt} = \frac{e^{W_{bt}-W_{b1}}}{\sum_i e^{W_{it}-W_{b1}}} \tag{8}$$

For $t > 1$ with $Z_{b1} = 1/A$. D_{ab} and Z_{bt} represent the most that can be identified from data on residential mobility (though other normalizations are possible). Using (7) and (8), (6) can be written as:

$$p_{abt} = \frac{D_{ab}Z_{bt}}{\sum_i D_{ai}Z_{it}} \tag{9}$$

We estimate this model by maximum likelihood. If the number of movers from a to b at time t is M_{abt} the log-likelihood can be written (up to a constant that does not depend on parameters) as:

$$\log L = \sum_{a,b,t} M_{abt} \log p_{abt} \tag{10}$$

which can be maximized over D_{ab} and Z_{bt} subject to the constraints that D_{ab} sums to one for all a and Z_{bt} to one for all $t > 1$. Using (9), (10) can be written as:

$$\log L = \sum_{a,b} logD_{ab}\left(\sum_t M_{abt}\right) + \sum_b logZ_{bt}\left(\sum_{a,t} M_{abt}\right) - \sum_{a,t} log\left(\sum_i D_{ai}Z_{it}\right)\left(\sum_b M_{abt}\right) \tag{11}$$

(11) is estimated by maximum likelihood. If there are A areas and T time periods this likelihood function contains A(A-1) parameters in D_{ab} and (A-1) (T-1) parameters in Z_{bt} (all after allowing for the normalization), approximately 99.5m parameters, so that estimation is not entirely straightforward. But an iterative algorithm can be used as, conditional, given an initial set of parameters one can update the parameters using a simple closed-form expression and this process converges to the ML estimates. The estimates of D_{ab} and Z_{bt} that emerge from

this model are simply a large set of fixed effects that can be thought of as one way of describing the residential mobility flows.

Once these fixed effects are estimated we then model them. We discuss the modelling of D_{ab} and Z_{bt} separately.

c. The Modelling of D_{ab}

One could simply interpret D_{ab} as a time-invariant fixed effect in which case there is nothing more to estimate. But one might be interested in, for example, how the probability of moving between areas is affected by the distance between them. In estimating such a model we need to take account of the normalization that D_{ab} adds to one for every a so that an origin fixed effect is included. And the specification in (7) shows that it is also affected by W_{b1} so that a destination fixed effect needs to be included.

Because the elements of D_{ab} can be thought of as a probability as they are non-negative (though there are many zeroes) and sum to one for each a, it is natural to think of estimating this by a multinomial logit model. However, given the size of the matrix this is not feasible so we exploit the equivalence between the multinomial logit model and the Poisson. As shown by Aitkin and Francis (1992)[14], there is an equivalence between the multinomial logit model and the Poisson model as long as the Poisson model includes a fixed effect related to the unit across which the probabilities sum to one (here, the origin fixed effect).

So we assume that D_{ab} can be written as:

$$D_{ab} = \frac{e^{\alpha_a + \beta_b + f\left(dist_{ab}\right)}}{\sum_i e^{\alpha_a + \beta_i + f\left(dist_{ai}\right)}} \tag{12}$$

Where $f\left(dist_{ab}\right)$ is some function of the distance between a and b. The presence of two fixed effects means that this is not completely straightforward to estimate so we use an iterative procedure as described by Guimaraes and Portugal (2009). This iterative procedure involves treating the fixed effects as offsets in a Poisson model, and then estimating the effect of distance. Then, using the estimated effects of distance one re-computes the ML estimates of the fixed

[14] Other works have been also studying the equivalence of multinomial logit and Poisson models, as Palmgren (1981), Baker (1994), Lang (1996), and Guimaraes, Figueiredo, and Woodward (2003).

effects (there is a closed-form solution for this) and then uses those new fixed effects to re-estimate the effects of distance. This process converges to the ML model though it can be slow. The iterative procedure does not lead itself to direct estimates of standard errors so we follow Guimaraes and Portugal (2009) in reporting LR tests.

Given the time-consuming nature of estimating (12) with origin and destination fixed effects, it is not easy to simply experiment with the appropriate function of distance in (12). We estimate a linear and a quadratic model and then a model where the function is the log of distance as this seems reasonably close to the raw data presented in Figure 7 - Figure A1 in the Appendix shows the relation between the percentage of movers and distance seems quite linear in a logarithmic scale for very short distances, while its nonlinearity increases looking at longer distances.

Table 2 shows the results of models of the relation between distance and inflows. All models are Poisson regressions containing both destination and origin fixed effects. We start from a linear form for distance, and we find that a 1 km increase in the distance between two areas reduces the probability of moving between them by 4.4 percent. This is a big effect, but it is actually not that implausible given the short distance of most residential moves seen in Figure 7 that most of the people who move do so between areas that are in close proximity. The other feature that Figure 7 points out is that the relationship between distance and the probability of moving is highly non-linear. Column (2) shows the same model with a second degree polynomial of distance. Column (3) estimates the model using a logarithmic distance. The estimated coefficient is very big, mimicking the initial steepness that Figure 7 shows. Figure 8 compares the fit of the three functional forms relation of distance with outflow shares, with the D_{ab} decomposition, and with the linear and logarithmic predictions showed in Table 2[15]. The logarithmic model appears to better approximate the relation between outflows and distance with respect to the 'linear' version, we will therefore include the logarithmic distance in the estimations that follow.

d. The Modeling of Z_{bt}

From (8) Z_{bt} can be interpreted as an estimate of the relative attractiveness of area *b* in year *t* relative to the base year. The estimated values of Z_{bt} contain no zeroes, because there are some

[15] The series are rescaled to take value 0 in the 0-1 km bin, therefore the plot shows the cumulative flow shares changes from the 0-1 km bin. The graph is trimmed at 100 km for the sake of clarity.

people who move to every area in every period. The definition in (8) implies that Z_{bt} sums to one in every period and is normalized on the initial value for every destination. In modelling Z_{bt} the former effect is captured through time dummies while the latter through the inclusion of a destination fixed effect.

Because there are no zeroes – and all positive values - it is natural to take logs of Z_{bt} and then estimate as a linear regression form i.e. we have:

$$\log Z_{bt} = \log W_{bt} - \log W_{b1} + \delta_t \tag{13}$$

Sometimes, it is more convenient to estimate this in difference form i.e. to have:

$$\Delta \log Z_{bt} = \Delta \log W_{bt} + \Delta \delta_t \tag{14}$$

We model the attractiveness of destination areas as being a function for some regressors, x_{bt}, plus an error so that (14) can be written as:

$$\Delta \log Z_{bt} = \beta \Delta x_{bt} + \Delta \delta_t + \Delta \varepsilon_{bt} \tag{15}$$

The main destination characteristic that we are interested in is the unemployment rate in the destination area as a measure of the economic opportunity offered by residing in that area. But it is important to control for other factors both because the demographic mix of an area may itself affect the attractiveness of living in an area (an amenity effect) and because the unemployment rate itself will be affected by the demographic structure and our preferred measure of economic opportunity in an area should be purged of this.

This still leaves open how best to measure the economic opportunity offered by an 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 economic opportunity of local residents. 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 have to 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. This measure has the advantage that it is readily computed.

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 pay-offs 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 when there are questions about how forward-looking individuals are in making their decisions.

We prefer to simply condition on current measures of economic opportunity. Gallin (2004) showed that current conditions can be a sufficient statistic for future conditions if those conditions follow a Markov process. The interpretation of the coefficient on current conditions is unclear as it is a mixture of the impact of current and 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 estimated impact of the level of unemployment measured at the destination area on the probability of moving in that particular area. All models control for census years fixed effects and several characteristics measured at the ward of destination level, namely the population (in logarithm), age distribution[16], the percentage of married (or in a couple) individuals, the percentage of residents with a degree, the percentage of foreign born, and the percentage of full time students[17]. Column (1) shows, for reference, results when no area fixed effects are included. Unemployment appears to have essentially no relation with the inflows. This estimate is likely to be biased because of unobserved area characteristics correlated with the unemployment rate. The second column shows one way to handle this potential bias by including destination area fixed effects. In this specification the impact of

[16] The percentage of people aged less than 16 and more than 65 living in the area.
[17] This is the set of area level characteristics that will included in all models throughout the paper.

unemployment on inflows becomes significantly negative. A 1 percentage point increase in unemployment decreases the inflows by approximatively 0.8 percent from an average inflow over population that is of 9.62%.

Fixed effects do not solve for any bias related to time varying unobservables. We therefore also construct an Instrumental Variable for the unemployment rate. We use a Bartik-style shift-share instrument intended to capture local demand shocks. We use the fraction of employment in 6 industrial sectors in a t_0 year in each ward. To this we apply the national level growth in employment for each of those sectors[18] to get an estimate of the predicted employment growth in each year. In mathematical terms our employment instrument, EIV_{at}, is constructed as follows:

$$EIV_{at} = \sum_i e_{it_0a} \left(\log E_{it} - \log E_{it-1} \right) \tag{16}$$

Where e_{it_0a} is the share of people employed in industry i in area a at the initial time t_0, while E_{it} is the national level employment for industry i at time t. The instrument is strong as shown in column (4) of Table 3. As expected, positive expected employment growth is associated with lower unemployment.

The Instrumental Variable estimates are shown in Column (3) — the impact of unemployment on inflows is now more negative, to a 1 percentage point increase in unemployment relates a 4 percent decrease in the level of inflows into an area.

Table 4 shows results of the model estimated in first differences. Results show a negative impact of unemployment growth on the inflows, which ranges from a 1.2 to a 4.5 percentage decrease in inflows. These results are similar to those in the levels specification in Table 3. As a robustness check Table A1 follows Jaeger et al. (2018) include in the instrumental variable model also the lagged unemployment rate, instrumented with the lagged unemployment rate. Lagged unemployment has a negative impact on inflows, as expected. The lagged unemployment rate has an impact that is slightly higher than the current one, in the instrumental variable model, highlighting the importance of long term dynamics in studying the residential mobility patterns.

[18] Data used to construct initial shares are from 1971 Census of Population (source: Casweb). The sectors are the ones available in the public version of the data: agriculture, mining, manufacturing, construction, transports and utilities, and services. National level time series are from the Bank of England data collection (BoE, A Millennium of Macroeconomic Data for the UK, Table A53 Employment by Industry).

e. Does the Impact of Unemployment Vary With Distance?

Our procedure has decomposed the raw flow data into two parts – a pair fixed effect and a destination-time fixed effect. We have then estimated them separately. The ability to include a pair fixed effect is very useful but there might be interesting and important interactions of, for example, distance, with destination area characteristics that cannot be handled within this set-up. To investigate these effects required estimating the in-migration model in one step. While conceptually simple, the practical problem in doing this is the high dimensionality of the dataset. Having more than 400 million observations and a great number of fixed effects – over 10000 area of origin and the same number of destinations – means that estimation is time-consuming even using estimation procedures as the one proposed by Guimaraes and Portugal (2009) that we used in Section 4.c.

One strategy to reduce the dimensionality and allow to take into account a more restrictive set of controls is to run models with origin-destination pairs fixed effects. This specification has the advantage that it allows inclusion of interactions between variables e.g. between distance and unemployment in the destination area.

Table 5 shows the results for the origin-destination fixed effects models run on the full dataset. These models mechanically leave out the area pairs that had no flow of movers in any of the 4 censuses considered. Whereas the previous estimates have a destination*time fixed effect that is then modelled separately, Table 5 estimates model the destination effect as a time-invariant fixed effect (subsumed within the origin-destination pair fixed effect) and time-varying destination area characteristics. Column (1) shows the results for a model that is closest to the one presented in Column (2) of Table 3: it contains time varying area level characteristics and area of destination fixed effects. This specification has a lower impact of unemployment on mobility than the results of Table 3 but it is still significantly negative. A 1 percentage point increase in unemployment at destination decreases the probability of moving to that area of 1.8 percent. In Column (2) we investigate the fact that this specification allows us to include interactions between distance (a characteristic of the origin-destination pair) and time-varying destination area characteristics. Although out main interest is in the impact of unemployment we include interactions of log distance with all the destination area characteristics included in the model. The results in column (2) suggest that the impact of unemployment at the very shortest distances is positive, but that the impact turns negative after 3.2km. Column (3) re-estimates the model of Column (1) accounting for the potential endogeneity of the destination level of unemployment using the Bartik shock as an instrument. To do this in a Poisson regression, we use a control function approach where the first stage residual is included as an additional control variable in the model. In this case the coefficient of the level of unemployment turns out to be positive, but not statistically different from zero. The first stage regression is presented in Column (4). As Column (2) showed, the impact of unemployment does seem to vary with distance, so Column (5) shows the equivalent results to column (2) but allowing for endogeneity (the corresponding first stage is presented in Column (6)). The estimates are similar to those found in Column (2).

Our models are estimated at ward level, a much smaller geographic area than most other studies have used. We investigated the robustness of our results to using more aggregated areas, namely Travel-to-Work Areas[19] that are constructed to be local labour markets (approximately equivalent to US Commuting Zones). In Table A2 of the Appendix we present the results obtained for Poisson models that includes both area of origin and area of destination fixed effects. In this case the impact of distance is even higher than the one estimated for the Ward level dataset, perhaps unsurprisingly given that TTWA are bigger areas. Results for the impact of unemployment and for the interaction term between unemployment and distance are comparable to the ones obtained with the Ward model with area pair fixed effects. However, standard errors are much larger and the estimates not statistically different from zero, suggesting that the use of very small areas offers advantages in having more variation.

f. The Out-Migration Model

Our estimates so far have only been about the determinants of migration into areas, the in-migration decision. We now consider the decision to leave an area, the out-migration decision. The determinants of in- and out-migration can be different (e.g. because of mobility costs), a point investigated by Monras (2018) on data from US metropolitan areas. As discussed earlier, we use the model in (4) as our model of out-migration. In this model the benefits from moving from the current to every other area are summarized by the inclusive value. This is very helpful as it reduces the returns to moving to a very large number of alternative areas to one summary statistic.

[19] We use 2001 TTWA definition.

The inclusive value, as written in (3) which using (5) can be written as:

$$I_{at} = \log \sum\nolimits_b e^{d_{ab} + W_{bt}} \tag{17}$$

Using (7) and (8) this can be written as:

$$\begin{aligned} I_{at} &= \log \sum\nolimits_b e^{d_{ab} - W_{b1}} e^{W_{bt} - W_{b1}} = \log \sum\nolimits_b D_{ab} Z_{bt} \left(\sum\nolimits_i e^{d_{ai} - W_{i1}} \right) \left(\sum\nolimits_i e^{W_{it} - W_{i1}} \right) \\ &= \log \sum\nolimits_b D_{ab} Z_{bt} + \log \left(\sum\nolimits_i e^{d_{ai} - W_{i1}} \right) + \log \left(\sum\nolimits_i e^{W_{it} - W_{i1}} \right) \end{aligned} \tag{18}$$

The first term on the second line can be computed from the estimates of the in-migration model earlier, combining the estimates from Z_{bt} and D_{ab} models showed in the previous sections. The second term on the second line is an area fixed effect and the final term is a time fixed effect. This shows how the inclusive value can be estimated up to an area and a time effect so can be used in a model of out-migration.

This Poisson model is easier to estimate than the choice of the specific location, due to the reduced dimensionality of the problem: one can only leave the current area whereas there a large number of potential areas one might move to. We model the outflows in a similar way to the inflows, so estimating a Poisson model for the count of people who left the area in the year before each census. Given that the location choice is being modelled as a two-step choice, where one chooses whether to move or not and then chooses where to locate, we take into account the nested structure of the problem by including an inclusive value computed from the inflow model as estimated in the last part of Section 3. This can be thought of as a weighted average of the utility from moving to every other area where the weights are the probability of moving to that area from the current area.

Results are presented in Table 6[20]. All models are estimated with area of origin fixed effects. Column (1) shows that higher unemployment in the origin area has a small but significant impact on the number of people leaving an area: the estimates suggest a 1 percentage point increase in unemployment translating into an approximately 0.4 percent increase in outflows. The coefficient on the inclusive value would be expected to be positive as a higher value of moving elsewhere should be associated with a higher rate of out-migration. However, column (1) may suffer from endogeneity bias. The second column shows the first stage when the origin

[20] We also show results that exclude the Inclusive Value in Table A3 of the Appendix. Unemployment estimated coefficients are very similar to the ones in Table 7. All models include clusters at the area of origin level. In Table A4 include in the model a predicted value based on the raw Z_{bt} and D_{ab} for all potential inflow areas, and we use the estimated inclusive value as an instrumental variable for it. Results for unemployment are again very similar to the Table 6 results.

unemployment rate is instrumented by the Bartik shock: the instrument has a lot of power. Columns (3) to (5) then use a control function approach (because the model is a Poisson regression) to correct for endogeneity of the unemployment rate. The three columns differ in the nature of the control function used – column (3) simply includes the level of the first stage residual, column (4) includes the quadratic residual and column (5) the residual interacted with the unemployment rate. In all cases, the impact of the origin-area unemployment rate is larger than in column (1) though the standard errors are larger as well. –a one percentage point increase in unemployment translates into an approximately 1.6 percent increase in outflows. The coefficient on the inclusive value in columns (3)-(5) now has the expected positive sign with a coefficient about 0.2, though the standard error is very large. The unemployment rate in potential destination areas affects outflows through the impact on the inclusive value implied by the results in Table 3 and the formula in (18). Combining the estimates of Table 3 and Table 6 implies that the impact of destination area unemployment on the out-migration rate is smaller than the impact of the origin area unemployment rate.

5. The Analysis of Individual Longitudinal Data

a. The Data

Although the Census flow data documents the residential moves for the entire population between small areas, the aggregate nature of the data means it 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 1991-2008 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 this year and in future years and answer a broad variety of questions. The geocoded version[21] of BHPS/UKHLS allows us to identify moves at a local level as in the Census data used earlier. BHPS/UKHLS

[21] 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

also have more qualitative information on residential mobility e.g. it asks about the reason for any move; it may be that unemployment has different effects on different types of moves and this can be explored though the reasons given are self-reported.

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. However, the census data is only available every 10 years when the BHPS/UKHLS data is annual. For this section we choose to use only 1991 area characteristics to model differences across areas rather than seek to exploit time series variation in those characteristics that is not available for almost all years in our sample.

Similar to the approach used in the first part of the paper, we model the mobility choice as a choice of whether to move or not followed by the choice of the specific area i.e. we continue to use a nested structure. We modify our model of individual utility, (5), to allow for an influence of individual characteristics. Specifically, we assume that the utility of individual i currently living in a but moving to b at time t can be written as:

$$V_{iabt} = \gamma_0 \left(dist_{ab} \right) + \gamma_1 \left(dist_{ab} \right) * q_{it} + \beta_0 x_b + \beta_1 x_b * q_{it} \qquad (19)$$

Where q_{it} are the characteristics of individual i at time t, x_b are area characteristics that, for the reasons given above, we assume to be time-invariant, and $dist_{ab}$ is the distance between a and b (modelled as earlier as the logarithmic distance between every pair of areas). The specification in (19) allows for an influence of individual and area characteristics but also the interaction between them.

In choosing the individual characteristics to investigate 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, Pissarides and Wadsworth (1989) discuss how unemployment may actually lower the probability of migration[22]. Working status appears to be an important driver of

[22] Bloze and Skak (2016) find a similar result for found for Denmark and also highlight the role of commuting as a potential substitute for moving. Confirming the fact that moving is costly and that this may represent a driver for the slow adjustments documented in the literature, recent evidence for Germany suggests that programmes that subsidise moving cost have positive effects on job matching (Caliendo, Kunn and Mahlstedt, 2017).

moving decisions. The individual characteristics that we include are gender, marriage status, age, education achievements, house tenure, and working status.

Some 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, on average, than stayers, they tend to be younger, and less likely to own a house or be in social housing. They are less likely to belong to any ethnic minority and less likely to be married. They also are more likely to be in a paid job.

b. Estimation

1. In-Migration

Although we have a multinomial logit model for choice of destination area conditional on moving, the large number of different possible choices means that we again rely on the multinomial-Poisson transformation (Baker, 1994) for a practical way to estimate. 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 (19) will be subsumed in the fixed effects so can be dropped from the estimated model. These level effects cannot be identified in any case: if a characteristic affects utility equally in all areas, a model of choice cannot identify this as the choice is based on a comparison of utility in different areas. But the interactions of distance and area characteristics with individual characteristics can be identified and this is the focus of our analysis. Our estimated models also include time-invariant destination fixed effects. However, when it comes to modelling the interaction between individual and area characteristics we only look at the interaction of the area unemployment and white share as there are too many area fixed effects to interact them all with individual characteristics.

The dimensionality of the problem makes it more difficult to estimate the model at the ward level using the same techniques as we used with the census data. For example, it is not so useful to use the decomposition in (9) because the smaller sample sizes mean that many elements Z_{bt} would be estimated to be zero so that the two-step analysis would not work as well[23].

[23] The approach of Bayer et al (2007) does something like the decomposition in (9) to estimate the average demand for a particular house but they can take advantage of the fact that all houses in their sample have the net demand of one household – there is no natural analogy for areas.

We use the 'big data bootstrap' procedure suggested in Kleiner et al. (2012), implemented as follows. We randomly create different subsamples of the over 10000 destination wards in the UK. Each subsample contains 253 areas, which is, approximately, N^{γ} with $\gamma = 0.6$ as suggested in Kleiner et al. (2012), and N being the total number of wards. For each ward i in each subsample I we keep information only on people from BHPS and Understanding Society who moved there from any origin – we therefore exclude all people moving to areas $j \in J, J \neq I$). The only origins excluded from the obtained matrix are the ones from where nobody ever moved to any area in the subsample I. Then we exclude areas in the subsample I where no people or just one person ever moved, as they 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 as previously. Coefficients, bootstrapped standard errors, and Likelihood Ratio tests are then derived as weighted averages of the estimates from each run of the model estimated[24].

Table 8 shows results for the models that includes interaction terms between our area variables of interest and the individual level characteristics: the models also include individual*time fixed effects, in line with the Multinomial-Poisson equivalence, and destination area fixed effects. The estimated baseline level of the cost of distance should be interpreted as the cost of distance for someone with baseline characteristics, assumed to be a 35 years old white man who has a low level of education, renting a house, not currently working, not married and with no children, and who is not a dependent child. Results confirm the strong impact on distance on the destination choice, with estimates similar to those found using Census data (see Table 2). But there is also significant heterogeneity in the effect of distance with individual characteristics. Older people, people in social housing, people who are working, and people who have children have a significantly higher estimated cost of distance meaning they are less likely to move long distances. People with a higher or middling levels of education are instead significantly more likely to move long distances, a higher education degree decreases the impact of distance by almost 48% with respect to a low level of education, while a mid-level degree decreases the impact by almost 32%[25].

Turning to the impact of unemployment, the inclusion of destination fixed effects means that the estimates are only informative about the heterogeneity of the response. These

[24] The results presented in this version derive from a 20 times replications of the described process.
[25] Notice that coefficients need to be exponentiated for interpretation.

heterogeneities in the response to unemployment rates are less striking than the heterogeneities in the response to distance, although there are some. Married people are relatively less likely to move to high unemployment, as are older people. Non-white people are relatively more likely to choose more high unemployment areas, as are those in social housing. There do not seem to be large differences by education.

Finally, there are significant heterogeneities in the propensity to move to areas with a high white share of the population. Women, married people, older people, people in social housing, people owning a house, people who are working, and people with children are more likely to move to areas with a higher incidence of white residents. Non-white people instead tend to move to less 'white' neighbourhoods. This is a factor that will tend to produce residential segregation by ethnicity but all that is estimated here is a relative preference: it is not possible with this data to say whether it is white people who prefer white areas or non-whites who prefer non-white areas. Also people with a higher education degree move less to 'white' neighbourhood, although the coefficient is only mildly significant (see also Langella and Manning, 2019, for an analysis of how the white share affects satisfaction with the neighbourhood).

Heterogeneity by Reason for Moving

BHPS/UKHLS also ask respondents about the reason why they move and there may be interesting heterogeneity by this factor although one must be cautious in interpreting the responses to these questions. We grouped the reasons for moving into 5 categories and 2 additional residual categories. The main reasons for moving are job related, home related, area related, family related, and education related. These 5 categories are not mutually exclusive, even though the overlap is quite minimal – approximatively 5 percent of our sample of movers give more than one reason. The most common reasons for moving are home-related reasons – 33.22 percent of the sample. 20.09 percent of the sample move for family-related reasons, 11.20 for job related reasons, 9.05 for reasons related to the area where living, and finally 6.14 for education reasons. We estimated our inflow model separately for each of these 5 reasons. Table 9 shows the estimated results. The role of distance differ quite a bit across specifications, having a higher baseline impact when the reason for moving is house, area or education related, implying that such moves are likely to be a shorter distance. Across all specifications more educated people tend to be less sensitive to distance, while the other interaction terms show quite a bit of heterogeneity across specification, suggesting that the underlying reason for moving is a relevant aspect in explaining the observed heterogeneities. In the appendix – Table A5 – we also show the same models estimated for 2 residual categories, the first groups together all respondents naming reasons that do not follow in the previous 5 categories, while the second is for respondents whose reason for moving is missing.

Household-Based Estimates

The estimates reported so far have been at the individual level as was the Census data used in the first part of the paper. However, individuals often move as part of households in which case household characteristics may be more relevant than individual characteristics. The BHPS/UKHLS allows us to identify complete households that move, of a total of 17,556 individuals who move at any point in time, 64.94% is related to a complete household move. This section reports estimates at a household level. The definition of a longitudinal identifier for the household is not so straightforward, as the survey only provides cross sectional household identifiers. So to construct the household panel we use a combination of individual longitudinal identifiers and the cross-sectional household identifiers. From household identifiers and the within-household relationships between individuals relationships we identify a unit household, that is the main individual or couple in the household[26]. We then follow the main individual/couple over time and we attach the same longitudinal household code to the same unit household. All individuals not belonging to the unit household are assigned to that according to the cross sectional household identifiers and will remain within the same longitudinal household identifier as long as they are in the same household as the unit. Based on this household definition we construct a set of variables at the household level[27] and we construct our definition of residential moves at the household level, counting households moves as ones where the household composition remains the same. For example, a couple will count as household unit a as long as they remain together: if they split up, there will be two new unit households, b and c, that we will subsequently follow separately. A mirroring example can be made for couple formation. In other words, all moves that involve a change in household composition will not appear as moves in the household panel, although they are there in the individual level panel that we presented in the previous Sections, all moves that

[26] We rely for the definition of main individual to the person number assigned by the survey, and for the definition of the couple we keep the main person and his/her spouse/partner, as defined by the cross-individual relationship codes provided by the survey.
[27] For instance, share of household members with a university degree, and share with high school degree, presence of children, maximum age, share of household members who are working, home ownership, and being in social housing.

keep the unit household stable will appear. This means we are not attempting to model household formation and dissolution. Table 10 summarizes the nature of the data – for example, the first row shows that 93.8% of movers are initially in a single household remain single after the move but 6.18% become part of a couple. For movers who are initially part of a couple, the second row shows that 95.66% remain part of the same couple, 3.12% become single and 1.2% part of a different couple. Our sample of whole-household movers consists of those who are part of the same unit before and after the move.

Table 11 illustrates the results for the panel of households. Distance has an impact that is quite close to the individual level estimates. Similarly to the individual level case, households with a higher proportion of more educated people are less sensitive to distance. Households with children, with a higher share of workers, and who either own a house or are in social housing are instead more sensitive to distance than the baseline. Regarding the interactions with unemployment, households with children, with older members, with a higher non-white share and a higher share of workers, and households who own a house are less likely to move to high unemployment areas, while households in social housing are more likely to move to high unemployment areas, also the interactions with higher education levels show positive signs, although the coefficient for higher education degrees is not statistically different from zero. Finally, households with children, with a higher share non-white, and house owners tend to move to neighbourhoods with higher white prevalence, while 'more educated' households, and households in social housing tend to move less to neighbourhoods with higher white prevalence.

On the whole the household level and the individual level estimates are similar. The impact of distance is similar as are the heterogeneities with the level of education (although there are differences in the significance of the coefficients) and the impacts of working status, house tenure and ethnicity. There are also some differences e.g. the impact of the white share is different in the individual and household analyses although that is not our main focus of interest.

We now turn to an analysis of outflows.

2. Out-migration

Economic conditions and local characteristics are likely not only to affect the probability of picking a particular area, but also to affect the probability of moving away. In this section we estimate the probability of moving away from an area using the panel from BHPS and Understanding Society. In the census model described earlier, we used the in-migration model to compute an inclusive value to summarize the opportunities available by moving away from the current area.

To use exactly this approach would require computing an inclusive value for each individual in the sample whether they moved or not. This is not possible from the inflow model estimated at individual level because the fixed effects included are at the individual*year level and are not estimated for those who do not move. Accordingly, we use a first-order Taylor series approximation to the inclusive value (3) around the value in some base year. This leads to:

$$I_{at} \approx V_{aat} + \frac{\sum_b e^{V_{ab0}} \left(V_{abt} - V_{aat}\right)}{\sum_b e^{V_{ab0}}} = V_{aat} + \sum_b p_{ab0}\left(V_{abt} - V_{aat}\right) \quad (20)$$

Where p_{ai0} is the probability of moving from a to b in the base year. (20) 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 particular move.

To implement this we use the fact that the probability of moving declines with distance assuming the weights are proportional to the function $e^{f(dist_{ab}, x_{bit})}$ which is the estimated utility from moving in a particular area estimated in Table 8. The weights depend on the estimated cost of distance, but also on the individual level characteristics, as shown in Table 8. We then use these weights to compute a weighted average of unemployment rates and white share in surrounding areas we then include in our main model the difference between the area characteristics in the place where living and the weighted average of the characteristics of all the other areas. The probability of moving at time t is therefore a function of the individual characteristics and of the difference between one's own area and other areas characteristics at time $t-1$. According to that, we estimate the probability of moving as a logistic function of individual and differences in area level characteristics between the origin area and potential destinations.

We show the results in Table 12, Column (1) includes only time fixed effects, while Column (2) includes individual fixed effects in which case the impact of area characteristics comes from individuals who move more than once in the sample. The impact of the time-varying individual characteristics is similar both with and without individual fixed effects. Turning to the impact of area characteristics, higher unemployment in the origin area relative to potential destination areas is significantly positively related to the probability of moving away from an area, as one would expect. This impact is slightly larger in the specification with individual fixed effects.

The impact of most other area characteristics are not significant once individual fixed effects are included.

One may be interested in understanding whether the drivers are more on the area of origin side or whether people are more strongly attracted by the characteristics of other areas. For this reason we include in the Appendix (Table A6) models that include area of residence characteristics and other areas average characteristics as separate variables. Another possibility is to estimate the model by keeping the area of origin area characteristics and including in the model the Inclusive Value estimated from the destination choice modelled in Table 8. We do so in the Appendix (Table A7) finding similar results once individual fixed effects are taken into account. Also in this case we show models with no fixed effects as well as individual fixed effects.

Similarly to what we did for the in-migration analysis, we try to see if there is any significant interaction between area and individual level characteristics. We therefore include in out logit model a full set of interactions between individual and area level characteristics. Table 13 displays the results for a subset of the interactions terms[28], namely the interactions with unemployment and with the white share. These specifications are highly demanding, so we expect a degree of noise in the results. Nevertheless some heterogeneities emerge. For instance women and people with children are less sensitive to the unemployment in the area, while for married people it appears to matter more.

We also run similar models to the ones of Table 12 for the out-migration decision estimated on the household level data. We present results in Table 14. At the household level unemployment seem to matter more for the choice of moving once household fixed effects are taken into account (Column 2).

Conclusions

This paper investigates the impact of economic conditions on residential mobility in the UK, focusing on developing an empirical method that can handle a large number of areas, allowing greater insight than can be obtained when using a higher level of geographical aggregation such as regions.

[28] We exclude some variables from Table 13 for the sake of readability.

Our main result is that most residential moves are very local and that the local 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. The magnitude of the inflow and outflow effects is quite comparable in our findings, a 1 percent increase in unemployment in one area decreases the inflow from 1.5 to 4 percent in our instrumental variable models, while it increases outflow by about 1.6 percent.

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.

References

Aitkin, M. and Francis, B. (1992). “Fitting the multinomial logit model with continuous covariates in GLIM”, *Computational Statistics & Data Analysis*, vol. 14, no. 1, pp. 89-97

Amior, M. and Manning, A. (2018) "The persistence of local joblessness", *American Economic Review*, no. 108, vol. 7

Amior, M. and Manning, A. (2019) "Migration, Commuting, and Local Joblessness"

Arcidiacono, P. and Ellickson, P.B., (2011). “Practical Methods for Estimation of Dynamic Discrete Choice Models”, *Annual Review of Economics*, vol. 3, pp. 363-39

Baker, S. G. 1994. “The multinomial-Poisson transformation”, *The Statistician, Journal of the Royal Statistical Society,* vol. 43, pp. 495–504

Bayer, P., Ferreira, F., and McMillan, R. (2007). “A Unified Framework for Measuring Preferences for Schools and Neighborhoods”, *Journal of Political Economy*, vol. 115, no. 4, pp. 588-638

Blanchard, O. and Katz, L.F. (1992). “Regional Evolutions”, *Brookings Papers on Economic Activity*, no. 1, pp. 1-75

Bloze, G. and Skak, M. (2016). “Housing equity, residential mobility and commuting”, *Journal of Urban Economics*, vol. 96, no. C, pp. 156-165

Bound, J. and Holzer, H. J. (2000). “Demand Shifts, Population Adjustments, and Labour Market Outcomes during the 1980s”, Journal of Labour Economics, vol. 18, no. 1, pp. 20-54

Caliendo, M., Künn, S. and Mahlstedt, R. (2017). "The return to labor market mobility: An evaluation of relocation assistance for the unemployed", *Journal of Public Economics*, vol. 148, no. C, pp. 136-15

Coen-Pirani, D. (2010). “Understanding Gross Worker Flows across US States”, *Journal of Monetary Economics*, vol. 57, pp. 769-784

Dahl, G.B. (2002) "Mobility and the Return to Education: Testing Roy Model with Multiple Markets", Econometrica, vol. 70, pp. 2367-2420

Dao, M., Furceri, D., and Loungani, P. (2017). “Regional Labor Market Adjustment in the United States: Trend and Cycle”, *The Review of Economics and Statistics*, Vol. 99, pp. 243-257

Dauth, W., Findeisen, S., Moretti, E., Suedekum, J. (2018). “Matching in Cities”, NBER Working Paper No. 25227

Decressin, J, and Fatas, A. (1995). “Regional labor market dynamics in Europe”, *European Economic Review*, Vol. 39, no. 9, pp. 1627-1655

Fetzer, Thiemo (20180. “Did austerity cause Brexit?”, Warwick Economics Research Papers, no. 1170, forthcoming *American Economic Review*

Gallin, J.H. (2004). "The long-run relationship between house prices and rents", Finance and Economics Discussion Series 2004-50, Board of Governors of the Federal Reserve System (US)

Ganong, P., Shoang, D., (2017). “Why has regional income convergence in the US declined?”, *Journal of Urban Economics*, vol. 102, pp. 76-90

Greenwood, Michael J., (1997), “Internal migration in developed countries”, ch. 12, p. 647-720 in Rosenzweig, M. R. and Stark, O. eds., *Handbook of Population and Family Economics*, vol. 1, Part B

Guimaraes, P., (2004). "Understanding the multinomial-Poisson transformation" *Stata Journal*, StataCorp LP, vol. 4, no. 3, pp. 1-9.

Guimaraes, P., O. Figueiredo, and D. Woodward (2003). “A tractable approach to the firm location decision problem”, *Review of Economic and Statistics,* vol. 85 no. 1, pp. 201–204

Guimaraes, P.O. and Portugal, P. (2009). “A Simple Feasible Procedure to fit Models with High-Dimensional Fixed Effects”, *The Stata Journal*, vol. 10, no. 4, pp. 629-649

Henley, A. (1998). “Residential Mobility, Housing Equity and the Labour Market”, *The Economic Journal*, vol. 108, no. 447, pp. 414–427

Hughes, G. and McCormick, B. (1981). “Do Council Housing Policies Reduce Migration between Regions?”, *The Economic Journal*, 91, issue 364, p. 919-37

Hughes, G. and McCormick, B. (1985). “An empirical analysis of on-the-job search and job mobility”, *Manchester School*, vol. 53, pp. 76-95

Hunt, J. (2006). “Staunching Emigration from East Germany: Age and the Determinants of Migration”, *Journal of the European Economic Association*, vol. 4, no. 5, pp. 1014-1037

Jackman, R. and Savouri, S. (1992). “Regional Migration in Britain: An Analysis of Gross Flows Using NHS Central Register Data”, *The Economic Journal*, vol. 102, no. 415, pp. 1433-1450

Jaeger, D.A., Ruist, J., and Stuhler, J. (2018). “Shift-share instruments and the impact of immigration”, NBER Working Paper no. 24285

Kaplan, G., Schulhofer-Wohl, S. (2017). “Understanding the long-run decline in interstate migration”, International Economic Review, vol. 58, n. 1, pp. 57-94

Kennan, J. and Walker, JR (2011) "The Effect of Expected Income on Individual Migration Decisions", Econometrica, vol. 79, no. 1, pp. 211-251

Kleiner, A., Talkawar, A., Sarkar, P., and Jordan, M. (2012). “The Big Data Bootstrap”, Appearing in *Proceedings of the 29 th International Conference on Machine Learning*, Edinburgh, Scotland, UK

Lang, J. (1996). “On the comparison of multinomial and Poisson log-linear models”, *Journal of the Royal Statistical Society*, Series B, vol. 58, pp. 253–266

Langella, Monica and Alan Manning (2019), “Diversity and Neighbourhood Satisfaction”, *Economic Journal*, forthcoming.

Manning, A. and Petrongolo, B. (2017). “How Local Are Labor Markets? Evidence from a Spatial Job Search Model”, *American Economic Review*, vol. 107, no. 10, pp. 2877-2907

Molloy, R., Smith, C. L., and Wozniak, A. K. (2011). "Internal Migration in the United States." Journal of Economic Perspectives, 25 (3): 173-96

Molloy, R., Smith, C. L., and Wozniak, A. K. (2014). "Declining Migration within the U.S.: The Role of the Labor Market," NBER Working Papers 20065

Monras, J. (2018). "Economic Shocks and Internal Migration", CEPR Discussion Paper No. DP12977

Moretti, E. (2011). “Local Labour Markets” in Handbook of Labour Economics, Chapter 14, vol. 4, part B, pp. 1237-1313

OECD (2005), *OECD Employment Outlook 2005*, OECD Publishing, Paris, https://doi.org/10.1787/empl_outlook-2005-en

Overman, H. G. (2002). Neighbourhood Effects in Large and Small Neighbourhoods. Urban Studies, 39(1), 117–130

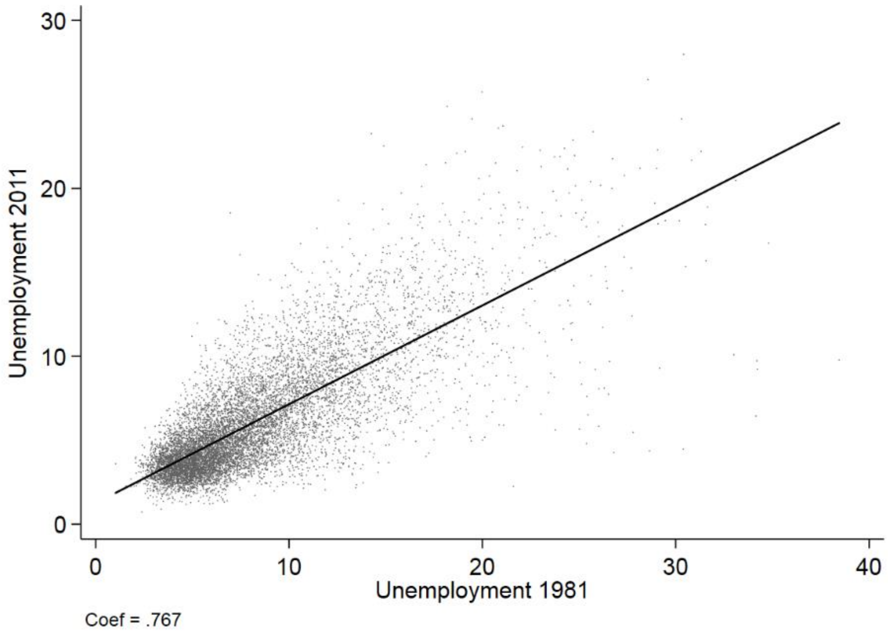
Palmgren, J. (1981). “The Fisher information matrix for log linear models arguing conditionally on observed explanatory variables”, *Biometrika,* vol. 68, pp. 563–566

Pissarides, C. A. and McMaster, I. (1990). “Regional Migration, Wages and Unemployment: Empirical Evidence and Implications for Policy”, Oxford Economic Papers, New Series, vol. 42, no. 4, pp. 812-831

Pissarides, C. and Wadsworth, J. (1989), “Unemployment and the Inter-regional Mobility of Labour”, *The Economic Journal*, vol. 99, no. 397, pp. 739-55

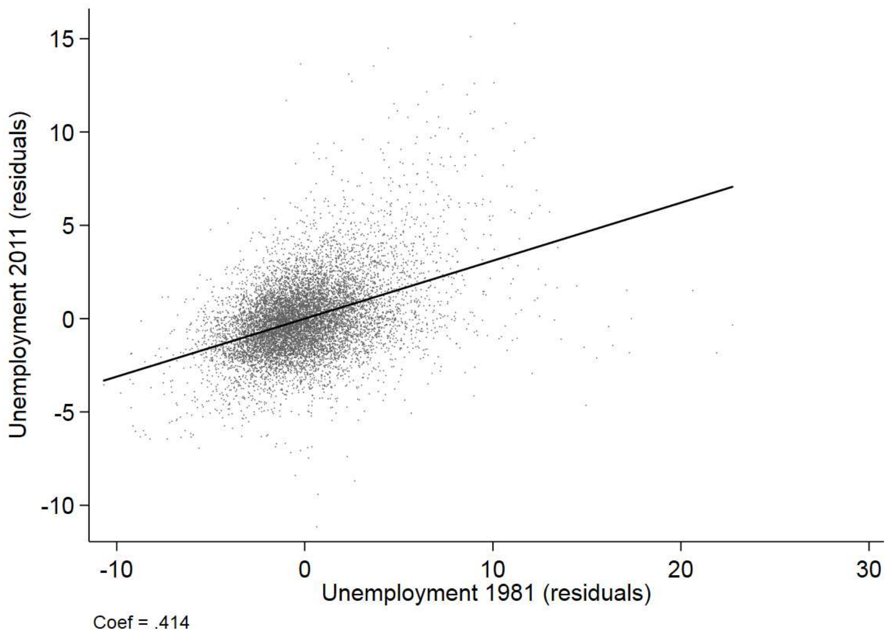
Figures

Figure 1. Unemployment rates over time. 1981 and 2011 census compared



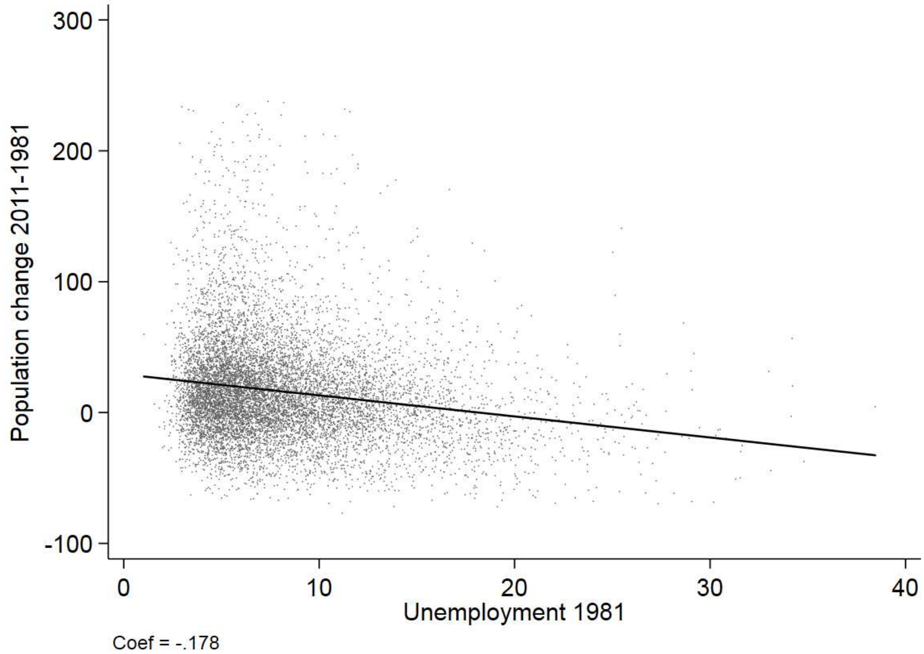
Note: Authors' elaboration of 1981 and 2011 census data at the CAS Ward level, Source: Nomis. Coef refers to the coefficient of the linear projection.

Figure 2. Unemployment rates over time. Controlling for demographic characteristics of the areas. 1981 and 2011 census compared



Note: Authors' elaboration of 1981 and 2011 census data at the CAS Ward level, unemployment in 2011 and 1981 are residualised from models that include controls for age distribution, marriage distribution, foreigners, incidence of students, and education; Source: Nomis. . Coef refers to the coefficient of the linear projection.

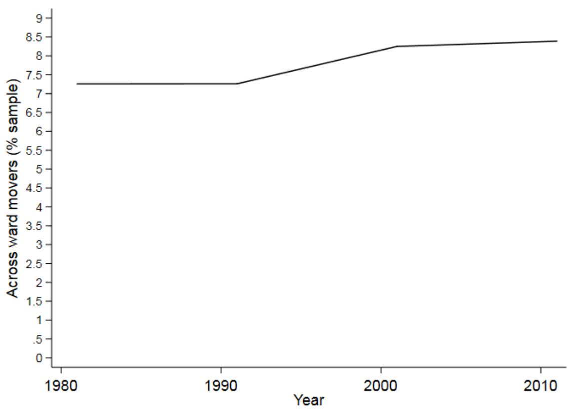
Figure 3. Changes in net population and 1981 unemployment rates



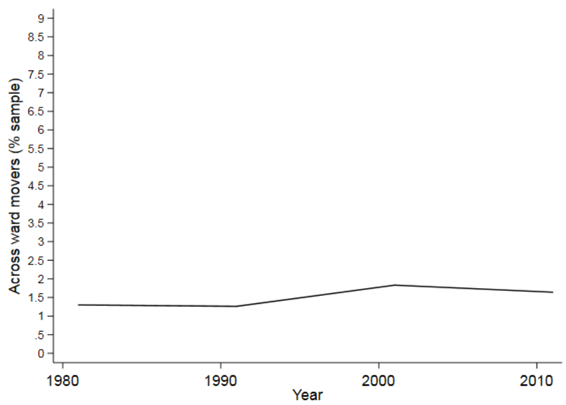
Note: Authors' elaboration of 1981 and 2011 census data at the CAS Ward level, Source: Nomis. Coef refers to the coefficient of the linear projection.

Figure 4. Percentage of population who moved. Census data

Panel A. Across wards moves

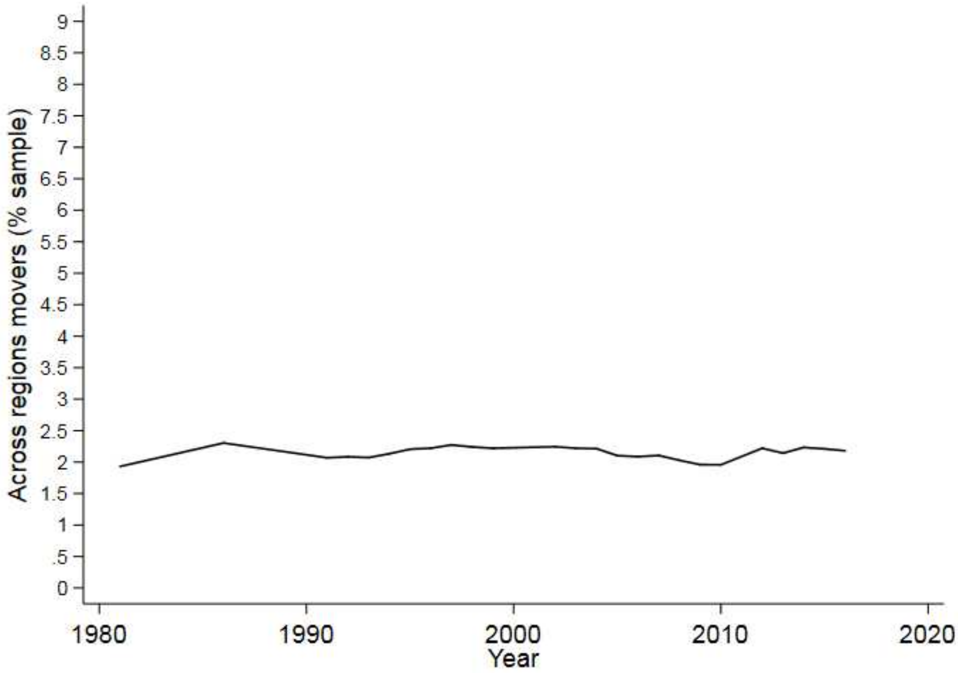


Panel B. Across regions moves



Note: Authors' elaboration of 1981-2011 Census of Population Data

Figure 5. Percentage of population who moved across regions. NHS Register data

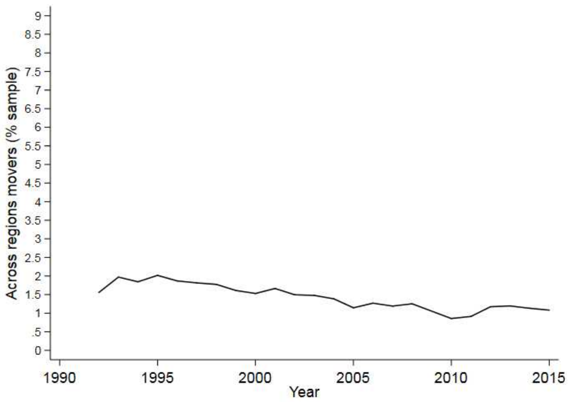


Note: Authors' elaboration of NHS Register Data

Figure 6. Percentage of population who moved. BHPS/Understanding Society data

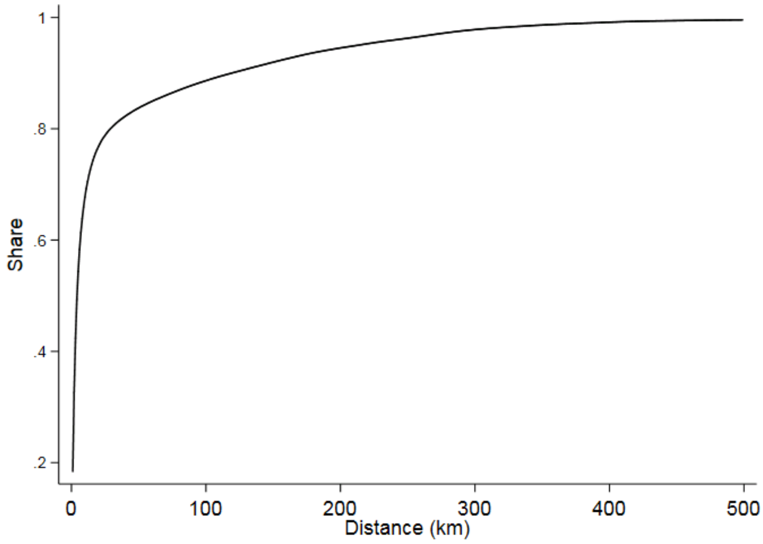
Panel A. Across wards moves

Panel B. Across regions moves



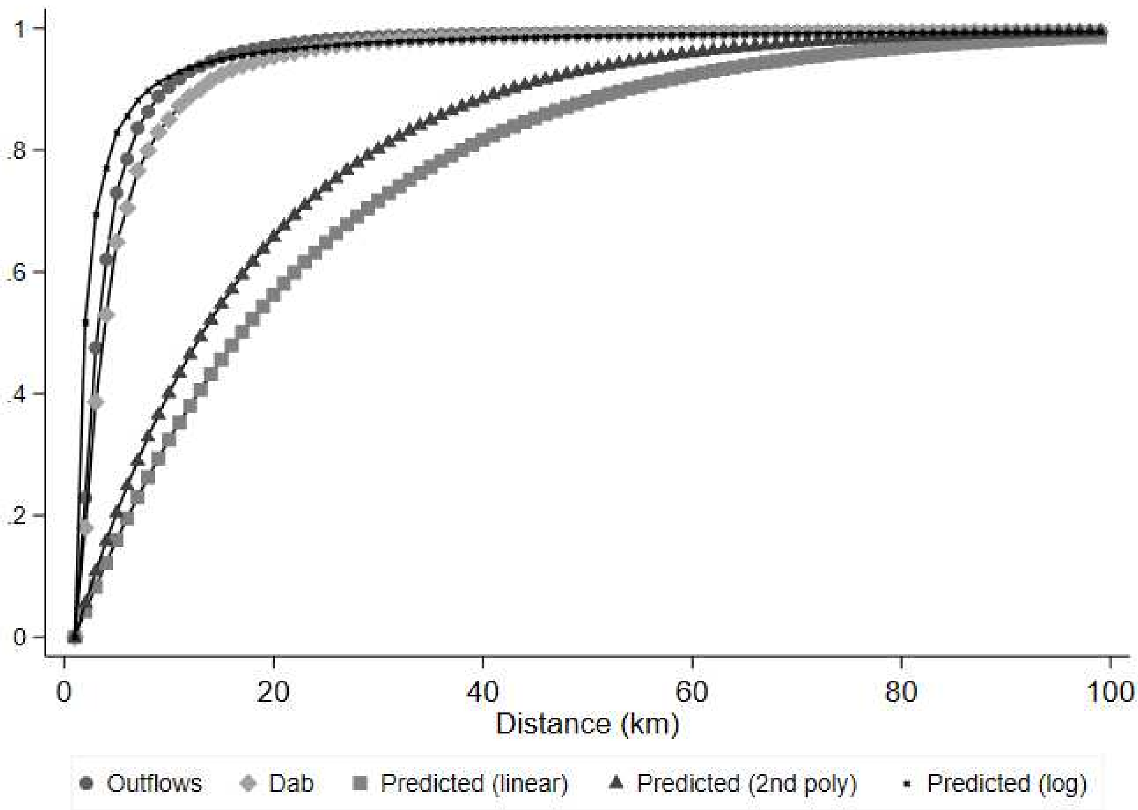
Note: Authors' elaboration of British Household Panel and Understanding Society data

Figure 7. Cumulative distribution of outflows in relation to distance. Average shares of outflows within each km bin



Notes: Percentage of people moving within a 1 km range. Trimmed at 500 km. Averages on 1981-2011 censuses of population

Figure 8. Distance and outflows. Predictions and outflows compared



Notes: The series are constructed as cumulative variations from outflows within 1 km, trimmed at 100 km. All predictions come from Poisson models that include origin and destination fixed effects. Predicted (linear) shows the obtained predictions for the model that includes distance in levels (corresponding to Column (1) of Table 2), Predicted (log) shows the predictions for the model that includes the log of distance (corresponding to Column (3) of Table 2).

Tables

Table 1. Aggregate data descriptives for the four census years. Unit of observation: CAS Ward

	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	5,581	4,032
Unemployment %	6.886	4.264
% of people below 16	19.923	3.817
% of people above 65	16.572	5.629
% of married	39.894	20.641
% of graduates	18.369	11.730
% of foreign born	6.535	7.767
% students (on population 16-64)	5.695	4.826
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), respectively, of the distance between two CASWards that have a non-zero flow of movers in the year before the census, both weighted by the number of people moving between the two areas.

Table 2. D_{ab} results. Poisson model. Destination and origin fixed effects

	(1) Linear	**(2) Quadratic**	**(3) Logarithmic**
Distance (km)	-0.0435***	-0.0574***	
	(0.0001)	(0.0002)	
Distance^2		0.0051***	
		(0.0000)	
Log of distance (km)			-1.9199***
			(0.0010)
N	101,425,041	101,425,041	101,425,041
LR test – Distance (km)	232.17	287.12	
LR test – Distance^2		275.52	
LR test – Log of distance			293.67

Note: *p<0.1, **p<0.05, ***p<0.01 Bootstrapped standard errors accounting for clusters at the destination area level in parenthesis. Model at the CAS Ward level. Distance measured as linear distance between CAS ward centroids, within wards distance is calculated as the average distance between two points in the centroid $\left(\frac{128\sqrt{area_i}}{45\pi^{1.5}}\right)$. Distance^2 is the distance squared divided by 100.

Table 3. The impact of unemployment on Z_{bt}. Dependent variable: logarithm of Z_{bt}

	(1) **OLS**	(2) **Destination FEs**	(3) **IV - Destination FEs**	(4) **First Stage**
Unemployment (%)	0.0002	-0.0076***	-0.0404***	
	(0.0008)	(0.0012)	(0.0071)	
Log of population	0.0173***	0.4124***	0.3991***	-0.4394***
	(0.0048)	(0.0151)	(0.0152)	(0.0793)
Population Below 16 (%)	-0.0059***	-0.0035**	-0.0003	0.1044***
	(0.0015)	(0.0015)	(0.0016)	(0.0087)
Population above 65 (%)	-0.0063***	-0.0123***	-0.0124***	0.0040
	(0.0010)	(0.0010)	(0.0010)	(0.0057)
Married/Couples (%)	-0.0046***	-0.0025***	-0.0011***	0.0388***
	(0.0003)	(0.0002)	(0.0004)	(0.0015)
Population with a degree (%)	-0.0009*	0.0009	-0.0005	-0.0591***
	(0.0005)	(0.0006)	(0.0007)	(0.0033)
People born abroad (%)	-0.0025***	0.0043***	0.0065***	0.0651***
	(0.0005)	(0.0010)	(0.0013)	(0.0058)
Students (%)	0.0174***	0.0152***	0.0148***	-0.0111**
	(0.0013)	(0.0015)	(0.0015)	(0.0054)
Bartik IV				-0.4987***
				(0.0189)
Constant	-8.9499***			
	(0.0647)			
Observations	40,284	40,284	40,280	40,280
R-squared	0.106	0.653	0.641	0.883

Note: *p<0.1, **p<0.05, ***p<0.01 Robust standard errors in parentheses, clustered at the destination area level. Models at the CAS Ward level. All regressions control for census years fixed effects. Unemployment is defined as the number of unemployed over the sum of workers and unemployed. Population below 16 and above 65, Married/Couples, and People born abroad, are percentage of total population in the CAS Ward. Population with a degree is the percentage of people with a Higher Education degree over population above 16. Students is calculated over population aged 16-64.

Table 4. The impact of unemployment on Zbt. First difference results. Dependent and all explanatory variables in first difference terms

	(1) Destination FEs	(2) IV - Destination FEs	(3) First Stage
Unemployment (%)	-0.0121***	-0.0465***	
	(0.0013)	(0.0107)	
Log of population	0.3516***	0.3272***	-0.6915***
	(0.0206)	(0.0199)	(0.2105)
Population Below 16 (%)	-0.0036**	-0.0020	0.0530***
	(0.0015)	(0.0016)	(0.0108)
Population above 65 (%)	-0.0109***	-0.0142***	-0.0889***
	(0.0012)	(0.0016)	(0.0087)
Married/Couples (%)	0.0002	0.0022***	0.0557***
	(0.0002)	(0.0006)	(0.0018)
Population with a degree (%)	0.0030***	-0.0003	-0.0943***
	(0.0008)	(0.0013)	(0.0051)
People born abroad (%)	0.0108***	0.0098***	-0.0458***
	(0.0012)	(0.0014)	(0.0086)
Students (%)	0.0142***	0.0141***	0.0045
	(0.0017)	(0.0017)	(0.0087)
Bartik IV			-0.3589***
			(0.0208)
Observations	30,213	30,210	30,210
R-squared	0.339	0.307	0.606

Note: *p<0.1, **p<0.05, ***p<0.01 Robust standard errors in parentheses, clustered at the destination area level. Models at the CAS Ward level. All regressions control for census years fixed effects. Unemployment is defined as the number of unemployed over the sum of workers and unemployed. Population below 16 and above 65, Married/Couples, and People born abroad, are percentage of total population in the CAS Ward. Population with a degree is the percentage of people with a Higher Education degree over population above 16. Students is calculated over population aged 16-64.

Table 5. Poisson model, origin-destination pair fixed effects. Dependent variable: area-to-area flows.

	(1) Poisson	(2) Poisson	(3) Poisson Control Function	(4) First Stage	(5) Poisson Control Function	(6) First Stage
Unemployment (%)	-0.0018***	0.0054***	0.0044		0.0082**	
	(0.0006)	(0.0009)	(0.0042)		(0.0041)	
Log distance*Unemployment (%)		-0.0046***			-0.0059***	
		(0.0003)			(0.0003)	
Log of population	0.6326***	0.6144***	0.6375***	-0.8798***	0.6144***	-0.0043
	(0.0065)	(0.0133)	(0.0070)	(0.0053)	(0.0141)	(0.0041)
Log distance*Log of population (%)		0.0026			0.0028	0.0020***
		(0.0038)			(0.0041)	(0.0004)
Population Below 16	-0.0109***	-0.0083***	-0.0119***	0.1734***	-0.0089***	-0.0043
	(0.0007)	(0.0013)	(0.0011)	(0.0005)	(0.0015)	(0.0041)
Log distance*Population below 16 (%)		-0.0009**			-0.0006	0.0020***
		(0.0004)			(0.0004)	(0.0004)
Population above 65 (%)	-0.0167***	-0.0098***	-0.0169***	0.0368***	-0.0101***	-0.0043
	(0.0005)	(0.0009)	(0.0005)	(0.0003)	(0.0010)	(0.0041)
Log distance*Population above 65 (%)		-0.0034***			-0.0032***	0.0020***
		(0.0003)			(0.0003)	(0.0004)
Married/Couples (%)	-0.0008***	-0.0010***	-0.0011***	0.0542***	-0.0010***	-0.0043
	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0041)
Log distance*Married/Couples (%)		0.0001***			0.0000	0.0020***
		(0.0000)			(0.0000)	(0.0004)
Population with degree (%)	0.0045***	0.0060***	0.0047***	-0.0516***	0.0062***	-0.0043
	(0.0003)	(0.0004)	(0.0003)	(0.0002)	(0.0004)	(0.0041)
Log distance*Population with degree (%)		-0.0007***			-0.0008***	0.0020***
		(0.0001)			(0.0001)	(0.0004)
People born abroad (%)	0.0071***	0.0074***	0.0068***	0.0462***	0.0070***	-0.0043
	(0.0004)	(0.0007)	(0.0004)	(0.0003)	(0.0008)	(0.0041)
Log distance*People born abroad (%)		-0.0002			-0.0000	0.0020***
		(0.0002)			(0.0002)	(0.0004)
Students (%)	0.0162***	0.0114***	0.0160***	0.0309***	0.0116***	-0.0043
	(0.0007)	(0.0011)	(0.0007)	(0.0002)	(0.0011)	(0.0041)
Log distance*Students(%)		0.0025***			0.0024***	0.0020***
		(0.0003)			(0.0003)	(0.0004)
First Stage residuals (from Bartik IV)			-0.0063		-0.0043	
			(0.0040)		(0.0041)	
First Stage residuals*Log distance					0.0020***	
					(0.0004)	
Bartik IV				-0.3731***		-0.3709***
				(0.0010)		(0.0013)
Observations	14,068,896	14,068,896	14,068,384	14,068,384	14,068,384	14,068,384

Note: *p<0.1, **p<0.05, ***p<0.01 Bootstrapped standard errors in parentheses. Models at the CAS Ward level. All regressions control for census years fixed effects, destination-origin pairs fixed effects. All control variables are measured at the destination area level. Unemployment is defined as the number of unemployed over the sum of workers and unemployed. Population below 16 and above 65, Married/Couples, and People born abroad, are percentage of total population in the CAS Ward. Population with a degree is the percentage of people with a Higher Education degree over population above 16. Students is calculated over population aged 16-64.

Table 6. Total outflow model. Poisson model with inclusive value.

	(1)	(2)	(3)	(4)	(5)
		First stage	Control Function	Control Function	Control Function
	Origin FEs	Origin FEs	Origin FEs	Origin FEs	Origin FEs
Unemployment (%)	0.0035**		0.0154**	0.0156*	0.0143
	(0.0016)		(0.0074)	(0.0086)	(0.0092)
Log of population	0.6277***	0.9225***	0.6160***	0.6149***	0.6151***
	(0.0145)	(0.0952)	(0.0158)	(0.0184)	(0.0193)
Population Below 16 (%)	-0.0124***	0.0832***	-0.0134***	-0.0134***	-0.0134***
	(0.0016)	(0.0077)	(0.0015)	(0.0015)	(0.0017)
Population above 65 (%)	-0.0138***	-0.0436***	-0.0133***	-0.0133***	-0.0132***
	(0.0012)	(0.0055)	(0.0012)	(0.0012)	(0.0012)
Married/Couples (%)	-0.0000	0.0132***	-0.0002	-0.0002	-0.0002
	(0.0002)	(0.0015)	(0.0002)	(0.0002)	(0.0003)
Population with a degree (%)	0.0056***	-0.0101***	0.0055***	0.0055***	0.0055***
	(0.0005)	(0.0032)	(0.0006)	(0.0006)	(0.0006)
People born abroad (%)	0.0056***	0.1519***	0.0038***	0.0038**	0.0039**
	(0.0009)	(0.0071)	(0.0014)	(0.0016)	(0.0018)
Students (%)	0.0115***	0.1593***	0.0096***	0.0096***	0.0097***
	(0.0012)	(0.0104)	(0.0016)	(0.0018)	(0.0017)
Bartik IV		-0.4342***			
		(0.0180)			
Inclusive Value	-0.0400	-19.8166***	0.1933	0.2001	0.1882
	(0.0592)	(0.6207)	(0.1459)	(0.1746)	(0.1847)
FS Residual			-0.0122*	-0.0121	-0.0145*
			(0.0071)	(0.0085)	(0.0085)
FS Residual^2				-0.0004	-0.0007
				(0.0006)	(0.0008)
FS Residual*Unemployment					0.0003
					(0.0002)
Observations	40,284	40,280	40,280	40,280	40,280

Note: *p<0.1, **p<0.05, ***p<0.01 Bootstrapped standard errors, accounting for clusters at the area of origin level, in parentheses. Models at the CAS Ward level. All regressions control for census years fixed effects. Unemployment is defined as the number of unemployed over the sum of workers and unemployed. Population below 16 and above 65, Married/Couples, and People born abroad, are percentage of total population in the CAS Ward. Population with a degree is the percentage of people with a Higher Education degree over population above 16. Students is calculated over population aged 16-64.

Table 7. British Household Panel Survey and Understanding Society. Descriptive statistics

	(1)	(2)
	Movers	**Not movers**
Women (%)	54.09	53.64
Married (%)	55.64	57.30
Not white (%)	8.15	14.76
Age	39.96	49.25
With Higher Education Degree (%)	29.61	25.85
With Mid-level Education (%)	32.37	24.04
Home owners (%)	65.67	72.80
Social housing (%)	15.85	19.04
Working (%)	64.90	51.93
Observations	168,081	361,081
Number of individuals	17,556	78,803

Note: Descriptives for the whole British Household Panel Survey and Understanding Society Panel data. Movers are defined as individuals who are ever observed in different CASWards in subsequent waves.

Table 8. Inflow estimates with British Household Panel Survey and Understanding Society data. Poisson model. Individual level data. Poisson models results.

	(1) Coefficients	(2) Bootstrapped SE	(3) t-stats+	(4) LR tests
Log of distance	-1.9297***	(0.0479)	[-39.874]	[164.813]
Log of distance ×				
Woman	-0.0557	(0.0374)	[-1.490]	[1.696]
Married	-0.0633	(0.0669)	[-0.983]	[2.902]
Non-white	0.0832	(0.1144)	[0.728]	[2.367]
Age	-0.0068***	(0.0021)	[-3.204]	[4.310]
Higher education	0.3905***	(0.0707)	[5.524]	[6.551]
Mid-level education	0.2758***	(0.0614)	[4.489]	[5.278]
Social housing	-0.3018***	(0.0992)	[-3.042]	[4.145]
Own house	0.0599	(0.0637)	[0.940]	[2.969]
Working	-0.4296***	(0.0526)	[-8.167]	[7.898]
Number of children	-0.1237***	(0.0378)	[-3.269]	[4.541]
Is dependent child	0.0322	(0.2771)	[0.170]	[2.067]
Initial unemployment ×				
Woman	0.0008	(0.0092)	[0.085]	[2.363]
Married	-0.0511***	(0.0173)	[-2.971]	[4.268]
Non-white	0.0530**	(0.0211)	[2.517]	[4.178]
Age	-0.0018***	(0.0006)	[-3.191]	[4.050]
Higher education	-0.0009	(0.0163)	[-0.057]	[3.307]
Mid-level education	0.0130	(0.0132)	[0.988]	[3.030]
Social housing	0.0531***	(0.0175)	[3.042]	[3.617]
Own house	-0.0038	(0.0161)	[-0.239]	[2.155]
Working	-0.0138	(0.0130)	[-1.063]	[2.775]
Number of children	0.0030	(0.0084)	[0.363]	[2.665]
Is dependent child	0.0167	(0.0440)	[0.387]	[2.210]
Initial share of white residents ×				
Woman	0.0058***	(0.0013)	[4.628]	[4.053]
Married	0.0135***	(0.0023)	[5.961]	[6.341]
Non-white	-0.0258***	(0.0040)	[-6.528]	[8.854]
Age	0.0005***	(0.0001)	[7.081]	[6.706]
Higher education	-0.0041*	(0.0023)	[-1.786]	[4.054]
Mid-level education	-0.0008	(0.0018)	[-0.442]	[2.930]
Social housing	0.0113***	(0.0027)	[4.202]	[4.677]
Own house	0.0038*	(0.0021)	[1.800]	[3.655]
Working	0.0170***	(0.0018)	[9.425]	[8.068]
Number of children	0.0033***	(0.0011)	[2.830]	[5.286]
Is dependent child	0.0053	(0.0076)	[0.723]	[3.348]

Note: *p<0.1, **p<0.05, ***p<0.01 Stars refer to bootstrapped standard errors t-statistics. + t-stats (Column 3) refer to the t-tests calculated on the bootstrapped SE. As described in Section 5, models are estimated on 20 different sub-sampling sets of the original dataset. Each set is made of 40 sub-samples of the dataset. Coefficients and standard errors presented in this table are averages of the estimates obtained from each model, weighted by the actual dimension of each sub-sample. Standard errors are bootstrapped accounting for clusters at the destination area level. Each model accounts for individual*year fixed effects and destination area fixed effects. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis).

Table 9. Inflow estimates with British Household Panel Survey and Understanding Society data. Poisson model. Individual level data. Poisson models by reason for moving (continues in the following page).

	(1)		(2)		(3)		(4)		(5)	
	Job-related		**House related**		**Area related**		**Family related**		**Education related**	
Log of distance	-1.4037***	(0.0206)	-2.2989***	(0.0179)	-2.0116***	(0.0329)	-1.8538***	(0.0199)	-2.1778***	(0.0553)
Log of distance ×										
Woman	-0.0384**	(0.0185)	-0.0117	(0.0137)	-0.0765***	(0.0250)	0.0625***	(0.0163)	0.0225	(0.0274)
Married	0.0573	(0.0425)	-0.0911***	(0.0231)	-0.0887**	(0.0423)	0.1212***	(0.0281)	-0.2475*	(0.1272)
Non-white	0.2712***	(0.0600)	0.0427	(0.0316)	-0.2217*	(0.1143)	0.1584***	(0.0577)	0.3412***	(0.0669)
Age	-0.0090***	(0.0016)	-0.0028***	(0.0007)	0.0098***	(0.0016)	0.0081***	(0.0008)	-0.0611***	(0.0045)
Higher education	0.4867***	(0.0413)	0.1578***	(0.0242)	0.2582***	(0.0525)	0.2130***	(0.0340)	0.2342***	(0.0453)
Mid-level education	0.2890***	(0.0352)	0.0763***	(0.0227)	0.0541	(0.0483)	0.1511***	(0.0259)	0.0038	(0.0456)
Social housing	-0.0868	(0.0611)	-0.0776**	(0.0345)	-0.2578***	(0.0663)	-0.0494*	(0.0286)	0.0147	(0.0813)
Own house	0.1118***	(0.0365)	0.0830***	(0.0208)	-0.0294	(0.0561)	-0.1137***	(0.0257)	0.2403***	(0.0433)
Working	-0.1625***	(0.0283)	-0.1971***	(0.0171)	-0.2695***	(0.0442)	-0.1733***	(0.0229)	-0.0006	(0.0566)
Number of children	-0.0507**	(0.0245)	-0.0490***	(0.0138)	-0.1255***	(0.0293)	-0.0970***	(0.0146)	-0.0249	(0.0231)
Is dependent child	0.4340**	(0.1752)	-0.0747	(0.0138)	0.2901	(0.2661)	-0.0530	(0.0629)	0.1124**	(0.0567)
Initial unemployment ×										
Woman	-0.0085	(0.0064)	-0.0038	(0.0030)	-0.0156**	(0.0074)	-0.0065	(0.0053)	0.0206***	(0.0075)
Married	-0.0692***	(0.0166)	-0.0461***	(0.0070)	-0.0666***	(0.0157)	-0.0248***	(0.0091)	-0.1242***	(0.0407)
Non-white	0.0561***	(0.0142)	0.0469***	(0.0046)	0.0890***	(0.0190)	0.0537***	(0.0075)	0.0176	(0.0133)
Age	-0.0020***	(0.0005)	-0.0012***	(0.0002)	0.0003	(0.0004)	-0.0011***	(0.0002)	-0.0099***	(0.0007)
Higher education	-0.0120	(0.0102)	-0.0125***	(0.0040)	-0.0254	(0.0155)	-0.0224**	(0.0090)	0.0284**	(0.0145)
Mid-level education	-0.0170**	(0.0077)	0.0053	(0.0046)	0.0049	(0.0131)	-0.0054	(0.0068)	0.0214**	(0.0106)
Social housing	0.0545***	(0.0130)	0.0078*	(0.0046)	-0.0216	(0.0151)	0.0515***	(0.0069)	0.0063	(0.0200)
Own house	0.0032	(0.0100)	-0.0595***	(0.0064)	-0.0967***	(0.0149)	-0.0210***	(0.0069)	0.0199**	(0.0101)
Working	-0.0101	(0.0086)	-0.0391***	(0.0032)	-0.0255**	(0.0116)	-0.0002	(0.0060)	0.0367***	(0.0115)
Number of children	-0.0128	(0.0081)	0.0027	(0.0026)	0.0170***	(0.0063)	0.0054	(0.0040)	0.0007	(0.0088)
Is dependent child	-0.0015	(0.0282)	-0.0501***	(0.0174)	0.0541	(0.0634)	0.0163	(0.0159)	-0.0022	(0.0104)

Table 9 (cont'ed). Inflow estimates with British Household Panel Survey and Understanding Society data. Poisson model. Individual level data. Poisson models by reason for moving (continues from page).

	(1) Job-related		(2) House related		(3) Area related		(4) Family related		(5) Education related	
Initial share of white residents ×										
Woman	0.0000	(0.0010)	0.0000	(0.0004)	0.0056***	(0.0010)	-0.0002	(0.0007)	-0.0003	(0.0014)
Married	0.0067***	(0.0025)	0.0070***	(0.0006)	0.0080***	(0.0020)	0.0006	(0.0014)	0.0192***	(0.0049)
Non-white	-0.0218***	(0.0031)	-0.0153***	(0.0011)	-0.0098**	(0.0044)	-0.0204***	(0.0023)	-0.0320***	(0.0026)
Age	0.0007***	(0.0001)	0.0002***	(0.0000)	-0.0001	(0.0001)	-0.0000	(0.0000)	0.0028***	(0.0001)
Higher education	-0.0246***	(0.0018)	-0.0039***	(0.0007)	0.0008	(0.0022)	-0.0030**	(0.0013)	-0.0017	(0.0024)
Mid-level education	-0.0141***	(0.0017)	-0.0036***	(0.0006)	0.0031*	(0.0018)	-0.0020*	(0.0010)	0.0010	(0.0023)
Social housing	0.0010	(0.0026)	-0.0012	(0.0008)	0.0121***	(0.0025)	-0.0061***	(0.0010)	0.0064	(0.0041)
Own house	-0.0046**	(0.0019)	0.0055***	(0.0008)	0.0129***	(0.0021)	0.0042***	(0.0010)	-0.0057***	(0.0021)
Working	0.0062***	(0.0014)	0.0062***	(0.0005)	0.0117***	(0.0017)	0.0029***	(0.0010)	0.0038	(0.0025)
Number of children	0.0033***	(0.0012)	0.0009**	(0.0004)	0.0005	(0.0010)	0.0018***	(0.0006)	0.0026**	(0.0011)
Is dependent child	-0.0141	(0.0096)	0.0093***	(0.0029)	0.0071	(0.0098)	-0.0036	(0.0024)	-0.0029	(0.0032)
N	1,553,085		18,776,058		963,770		4,759,743		369,334	

Note: *p<0.1, **p<0.05, ***p<0.01 Standard errors are bootstrapped accounting for clusters at the destination area level. Each model accounts for individual*year fixed effects and destination area fixed effects. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis).

Table 10. Unit household changes matrix

	In the same unit t+1	Different single unit in t+1	Different couple unit at t+1	Total
Individuals in a single unit household at t	112,208	0	7,383	119,591
	(93.82)		(6.18)	(100)
Individuals in a couple unit household at t	300,206	9,804	3,812	313,822
	(95.66)	(3.12)	(1.21)	(100)

Note: Flows are calculated at the individual level and refer to the comparison between the household each individual is at wave t with the household where each individual is at wave t+1. As explained in Section 5.b.1 household is defined according to the main household respondent, as defined in the survey, and - if there is – his/her spouse/partner. Row percentages in parenthesis.

Table 11. Inflow estimates with British Household Panel Survey and Understanding Society data. Poisson model. Household level data. Poisson models results.

	(1)	(2)	(3)	(4)
	Coefficients	**Bootstrapped SE**	**t-stats+**	**LR tests**
Log of distance	-1.9675***	(0.0209)	[-94.138]	[117.216]
Log of distance ×				
Has children	-0.0004	(0.0058)	[-0.071]	[31.716]
Share with HE degree	0.5144***	(0.0185)	[27.754]	[27.417]
Share with high school degree	0.2265***	(0.0204)	[11.119]	[31.807]
Max age	0.0005	(0.0004)	[1.179]	[1.152]
Share not white	0.0047	(0.0187)	[0.253]	[0.217]
Share at work	-0.1272***	(0.0183)	[-6.950]	[32.774]
House owner	-0.1730***	(0.0152)	[-11.404]	[16.657]
Social house	-0.3412***	(0.0190)	[-17.916]	[15.695]
Initial unemployment ×				
Has children	-0.0033**	(0.0013)	[-2.513]	[2.417]
Share with HE degree	0.0053	(0.0044)	[1.226]	[1.176]
Share with high school degree	0.0119***	(0.0040)	[2.993]	[2.581]
Max age	-0.0011***	(0.0001)	[-11.727]	[11.535]
Share not white	-0.0207***	(0.0040)	[-5.215]	[31.783]
Share at work	-0.0213***	(0.0038)	[-5.547]	[-]
House owner	-0.0712***	(0.0049)	[-14.630]	[15.880]
Social house	0.0428***	(0.0043)	[10.025]	[9.311]
Initial share of white residents ×				
Has children	0.0003*	(0.0002)	[1.751]	[1.759]
Share with HE degree	-0.0180***	(0.0006)	[-29.078]	[25.258]
Share with high school degree	-0.0103***	(0.0007)	[-15.104]	[14.191]
Max age	0.0000	(0.0000)	[1.473]	[1.366]
Share not white	0.0038***	(0.0007)	[5.281]	[4.791]
Share at work	0.0011*	(0.0006)	[1.815]	[1.759]
House owner	0.0107***	(0.0007)	[15.364]	[16.737]
Social house	-0.0018***	(0.0007)	[-2.615]	[2.425]

Note: *p<0.1, **p<0.05, ***p<0.01 Stars refer to bootstrapped standard errors t-statistics. + t-stats (Column 3) refer to the t-tests calculated on the bootstrapped SE. Standard errors are bootstrapped accounting for clusters at the destination area level. Each model accounts for individual*year fixed effects and destination area fixed effects. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis).

Table 12. Outflow estimates with British Household Panel Survey and Understanding Society data. Logit model. Individual level data.

	(1)		(2)	
	Logit – Year FE		Logit – Year + Individual FE	
Individual characteristics				
Woman	-0.0366***	(0.0113)		
Married	-0.2522***	(0.0217)	-0.2285***	(0.0485)
Non-white	-0.2990***	(0.0332)		
Age	-0.0413***	(0.0006)	-0.0476	(0.0399)
Higher education	0.4172***	(0.0211)	0.4922***	(0.0905)
Mid-level education	0.2077***	(0.0186)	0.4471***	(0.0588)
Social housing	-1.1953***	(0.0318)	-0.6762***	(0.0693)
Own house	-1.4051***	(0.0241)	-0.8986***	(0.0512)
Working	-0.0617***	(0.0174)	-0.1312***	(0.0402)
Number of children	-0.1181***	(0.0106)	-0.1395***	(0.0264)
Is dependent child	-0.7291***	(0.0427)	-0.4075***	(0.0725)
Area characteristics (difference)				
Unemployment rate 1991	0.0135***	(0.0042)	0.0185*	(0.0108)
White share 1991	0.0047	(0.0041)	-0.0072	(0.0090)
Share of population under 16	-0.0142**	(0.0055)	-0.0064	(0.0127)
Share of population above 65	-0.0098**	(0.0038)	-0.0103	(0.0078)
Share of married/couples	0.0047***	(0.0016)	0.0027	(0.0042)
Share with a degree	0.0109***	(0.0027)	0.0038	(0.0060)
Share of people born abroad	0.0138**	(0.0069)	0.0185	(0.0138)
Share of students	-0.0147	(0.0096)	-0.0147	(0.0198)
N	376,367		120,615	

Note: *p<0.1, **p<0.05, ***p<0.01 All models account for clusters in the standard errors estimation at the destination area level. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis). Area level characteristics are obtained as the differences between the levels in one own area and the weighted averaged characteristics in all the other areas. Weights are constructed as individual specific utilities from moving into a specific area using the estimated coefficients from Table 8. All variables are lagged of one period with respect to the outcome.

Table 13. Outflow estimates with BHPS and Understanding Society data. Logit model. Individual level data. Models with interactions.

	(1)		(2)	
	Logit – Year FE		**Logit – Year + Individual FE**	
Unemployment 1991 (difference) ×				
Woman	-0.0103***	(0.0031)	-0.0132	(0.0133)
Married	0.0214***	(0.0059)	0.0178	(0.0207)
Non-white	0.0053	(0.0090)	0.0091	(0.0401)
Age	-0.0002	(0.0002)	0.0012	(0.0008)
Higher education	0.0121**	(0.0058)	-0.0046	(0.0224)
Mid-level education	0.0031	(0.0048)	-0.0144	(0.0166)
Social housing	0.0023	(0.0078)	0.0023	(0.0287)
Own house	0.0009	(0.0066)	0.0095	(0.0223)
Working	-0.0052	(0.0047)	-0.0108	(0.0159)
Number of children	0.0004	(0.0028)	-0.0087	(0.0089)
Is dependent child	-0.0066	(0.0104)	0.0416	(0.0354)
White share 1991 (difference) ×				
Woman	-0.0014	(0.0038)	-0.0092	(0.0135)
Married	-0.0041	(0.0038)	0.0028	(0.0234)
Non-white	0.0127***	(0.0040)	-0.0124	(0.0281)
Age	0.0002	(0.0001)	-0.0007	(0.0010)
Higher education	0.0017	(0.0034)	-0.0021	(0.0221)
Mid-level education	-0.0042	(0.0032)	-0.0005	(0.0206)
Social housing	-0.0097*	(0.0051)	-0.0128	(0.0316)
Own house	-0.0023	(0.0035)	0.0040	(0.0199)
Working	-0.0046	(0.0028)	0.0001	(0.0134)
Number of children	0.0006	(0.0017)	0.0084	(0.0111)
Is dependent child	-0.0037	(0.0058)	-0.0211	(0.0330)
N	376,367		120,615	

Note: *p<0.1, **p<0.05, ***p<0.01 All models account for clusters in the standard errors estimation at the destination area level. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis). Area level characteristics are obtained as the differences between the levels in one own area and the weighted averaged characteristics in all the other areas. Weights are constructed as individual specific utilities from moving into a specific area using the estimated coefficients from Table 8. All variables are lagged of one period with respect to the outcome. The models include all levels for both area and individual level characteristics. Only coefficients of the interactions are displayed for allowing easiness of reading.

Table 14. Outflow estimates with British Household Panel Survey and Understanding Society data. Logit model. Household level data.

	(1)		(2)	
	Logit – Year FE		Logit – Year + Household FE	
Individual characteristics				
Has children	-0.0764***	(0.0082)	-0.0615***	(0.0190)
Share with HE degree	0.4956***	(0.0316)	0.0644	(0.1644)
Share with high school degree	0.2355***	(0.0323)	0.0421	(0.1371)
Max age	-0.0395***	(0.0008)	0.0089	(0.0067)
Share not white	0.2739***	(0.0420)	0.0429	(0.3144)
Share at work	-0.3116***	(0.0274)	-0.2798***	(0.0654)
House owner	-1.5242***	(0.0273)	-1.2753***	(0.0869)
Social house	-1.2524***	(0.0347)	-0.7758***	(0.1046)
Area characteristics (difference)				
Unemployment rate 1991	0.0057	(0.0046)	0.0371***	(0.0141)
White share 1991	0.0071	(0.0042)	0.0076	(0.0142)
Share of population under 16	-0.0178***	(0.0057)	-0.0212	(0.0163)
Share of population above 65	-0.0104**	(0.0041)	-0.0188*	(0.0106)
Share of married/couples	0.0072***	(0.0017)	0.0055	(0.0057)
Share with a degree	0.0101***	(0.0029)	-0.0031	(0.0079)
Share of people born abroad	0.0164**	(0.0067)	0.0374*	(0.0220)
Share of students	-0.0229**	(0.0103)	0.0034	(0.0287)
N	230,085		59,408	

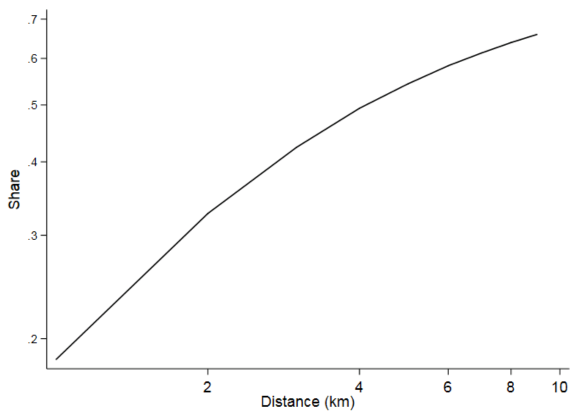
Note: *p<0.1, **p<0.05, ***p<0.01 All models account for clusters in the standard errors estimation at the destination area level. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis). Area level characteristics are obtained as the differences between the levels in one own area and the weighted averaged characteristics in all the other areas. Weights are constructed as household specific utilities from moving into a specific area using the estimated coefficients from Table 11. All variables are lagged of one period with respect to the outcome.

Appendix A

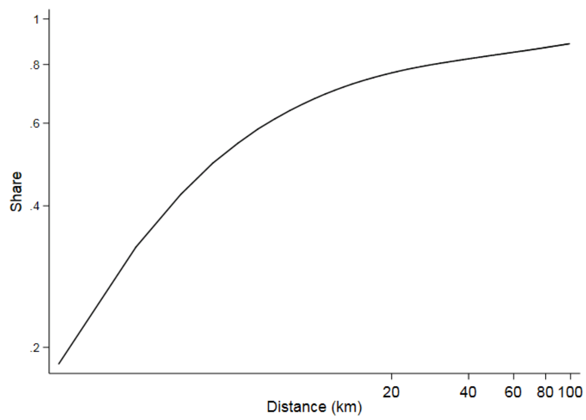
Figures

Figure A1. Cumulative distribution of outflows in relation to distance, log-log scale. Average shares of outflows within each km bin

Panel A. Trim at 10 km



Panel B. Trim at 100 km



Notes: Percentage of people moving within a 1 km range. Averages on 1981-2011 censuses of population

Tables

Table A1. The impact of unemployment on Zbt. With lagged unemployment rate and lagged Bartik IV

	(1) IV Destination FEs	(2) First Stage Unemployment	(3) First Stage Lagged Unemployment
Unemployment (%)	-0.0416***		
	(0.0071)		
Lagged Unemployment	-0.0552***		
	(0.0058)		
Log of population	0.4774***	-0.7822***	-0.7202***
	(0.0343)	(0.1985)	(0.1990)
Population Below 16 (%)	0.0072***	0.0279**	0.1980***
	(0.0022)	(0.0121)	(0.0119)
Population above 65 (%)	-0.0046**	-0.0453***	0.1768***
	(0.0018)	(0.0080)	(0.0082)
Married/Couples (%)	-0.0021***	0.0457***	-0.0356***
	(0.0005)	(0.0021)	(0.0018)
Population with a degree (%)	0.0067***	-0.0683***	0.0846***
	(0.0010)	(0.0046)	(0.0047)
People born abroad (%)	0.0058***	0.0009	0.0225***
	(0.0012)	(0.0062)	(0.0066)
Students (%)	0.0157***	-0.0209***	0.0443***
	(0.0018)	(0.0064)	(0.0061)
Bartik IV		-0.4980***	0.0215
		(0.0184)	(0.0210)
Lagged Bartik IV		-0.0615***	-0.6527***
		(0.0215)	(0.0258)
Observations	30,210	30,210	30,210

Note: *p<0.1, **p<0.05, ***p<0.01 Robust standard errors in parentheses, clustered at the destination area level. Models at the CAS Ward level. All regressions control for census years fixed effects. Unemployment is defined as the number of unemployed over the sum of workers and unemployed. Population below 16 and above 65, Married/Couples, and People born abroad, are percentage of total population in the CAS Ward. Population with a degree is the percentage of people with a Higher Education degree over population above 16. Students is calculated over population aged 16-64.

Table A2. Poisson model, origin and destination fixed effects. Travel-to-Work area estimates. Dependent variable: area-to-area flows.

	(1) Poisson	(2) Poisson	(3) Poisson Control Function	(4) First Stage
Unemployment (%)	-0.0080***	0.0288	0.0505	
	(.0034)	(.0316)	(.0310)	
Log of distance (km)	-2.8372***	-2.7502***	-2.7691***	
	(.0588)	(.0489)	(.0601)	
Log of distance *Unemployment (%)		-0.0123	-0.0060	
		(.0100)	(.0128)	
Log of population	0.9320***	0.8994***	0.8513***	0.0983**
	(.0559)	(.0645)	(.0526)	(.0477)
Population Below 16 (%)	-0.0140**	-0.0111	-0.0160*	0.0797***
	(.0062)	(.0074)	(.0086)	(.0053)
Population above 65 (%)	-0.0144***	-0.0147***	-0.0137***	-0.0115***
	(.0029)	(.0030)	(.0033)	(.0031)
Married/Couples (%)	-0.0007	-0.0004	-0.0004	0.0109***
	(.0006)	(.0006)	(.0007)	(.0007)
Population with a degree (%)	0.0030	0.0023	0.0034*	-0.0064***
	(.0028)	(.0024)	(.0019)	(.0014)
People born abroad (%)	0.0067**	0.0063**	-0.0018	0.1584***
	(.0027)	(.0028)	(.0036)	(.0025)
Students (%)	0.0290***	0.0297***	0.0325***	-0.0349***
	(.0026)	(.0028)	(.0030)	(.0020)
First Stage residuals (from Bartik IV)			0.1119**	
			(.0557)	
First Stage residuals*Log of distance			-0.0480**	
			(.0209)	
Bartik IV				-0.4030***
				(.0052)
Observations	215,296	215,296	215,296	215,296

Note: *p<0.1, **p<0.05, ***p<0.01 Standard errors in parentheses, clustered at the destination TTWA level. All regressions control for census years fixed effects, destination, and origin fixed effects. All control variables are measured at the destination area level. Unemployment is defined as the number of unemployed over the sum of workers and unemployed. Population below 16 and above 65, Married/Couples, and People born abroad, are percentage of total population in the CAS Ward. Population with a degree is the percentage of people with a Higher Education degree over population above 16. Students is calculated over population aged 16-64.

Table A3. Total outflow model. Poisson model with no inclusive value.

	(1) Origin FEs	(2) First stage Origin FEs	(3) Control Function Origin FEs	(4) Control Function Origin FEs	(5) Control Function Origin FEs
Unemployment (%)	0.0043***		0.0136*	0.0133*	0.0120*
	(0.0011)		(0.0078)	(0.0072)	(0.0072)
Log of population	0.6246***	-0.4394***	0.6279***	0.6280***	0.6280***
	(0.0152)	(0.0793)	(0.0157)	(0.0175)	(0.0147)
Population Below 16 (%)	-0.0125***	0.1044***	-0.0134***	-0.0133***	-0.0133***
	(0.0016)	(0.0087)	(0.0014)	(0.0016)	(0.0015)
Population above 65 (%)	-0.0137***	0.0040	-0.0137***	-0.0135***	-0.0135***
	(0.0011)	(0.0057)	(0.0011)	(0.0010)	(0.0010)
Married/Couples (%)	0.0000	0.0388***	-0.0004	-0.0004	-0.0004
	(0.0002)	(0.0015)	(0.0004)	(0.0003)	(0.0003)
Population with a degree (%)	0.0055***	-0.0591***	0.0059***	0.0059***	0.0058***
	(0.0006)	(0.0033)	(0.0007)	(0.0007)	(0.0007)
People born abroad (%)	0.0054***	0.0651***	0.0048***	0.0048***	0.0049***
	(0.0008)	(0.0058)	(0.0011)	(0.0010)	(0.0010)
Students (%)	0.0112***	-0.0111**	0.0113***	0.0113***	0.0113***
	(0.0011)	(0.0054)	(0.0014)	(0.0012)	(0.0011)
Bartik IV		-0.4987***			
		(0.0189)			
FS Residual			-0.0096	-0.0094	-0.0107
			(0.0077)	(0.0070)	(0.0069)
FS Residual^2				0.0004	0.0002
				(0.0004)	(0.0005)
FS Residual*Unempl.					0.0002
					(0.0002)
Observations	40,284	40,280	40,280	40,280	40,280

Note: *p<0.1, **p<0.05, ***p<0.01 Bootstrapped standard errors in parentheses, clusters at the area of origin level. Models at the CAS Ward level. All regressions control for census years fixed effects. Unemployment is defined as the number of unemployed over the sum of workers and unemployed. Population below 16 and above 65, Married/Couples, and People born abroad, are percentage of total population in the CAS Ward. Population with a degree is the percentage of people with a Higher Education degree over population above 16. *Students* is calculated over population aged 16-64.

Table A4. Total outflow model. Poisson model predicted value.

	(1) Origin FEs	(2) First stage Origin FEs	(3) First stage Origin FEs	(4) Control Function Origin FEs	(5) Control Function Origin FEs	(6) Control Function Origin FEs
Unemployment	0.0133***			0.0090	0.0099*	0.0114*
	(0.0012)			(0.0056)	(0.0053)	(0.0061)
Log of population	0.5446***	0.9225***	0.0272***	0.6087***	0.6025***	0.6017***
	(0.0148)	(0.0952)	(0.0042)	(0.0201)	(0.0215)	(0.0171)
Population Below 16	-0.0122***	0.0832***	-0.0000	-0.0118***	-0.0112***	-0.0112***
	(0.0012)	(0.0077)	(0.0004)	(0.0013)	(0.0012)	(0.0014)
Population above 65	-0.0115***	-0.0436***	0.0000	-0.0135***	-0.0130***	-0.0131***
	(0.0008)	(0.0055)	(0.0003)	(0.0009)	(0.0008)	(0.0009)
Married/Couples	0.0003*	0.0132***	-0.0000	-0.0003	-0.0002	-0.0002
	(0.0002)	(0.0015)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Population with a degree	0.0033***	-0.0101***	0.0010***	0.0056***	0.0055***	0.0055***
	(0.0005)	(0.0032)	(0.0001)	(0.0006)	(0.0006)	(0.0006)
People born abroad	0.0017**	0.1519***	0.0014***	0.0050***	0.0046***	0.0044***
	(0.0008)	(0.0071)	(0.0003)	(0.0015)	(0.0014)	(0.0015)
Students	0.0048***	0.1593***	0.0023***	0.0111***	0.0114***	0.0112***
	(0.0008)	(0.0104)	(0.0006)	(0.0016)	(0.0017)	(0.0016)
Predicted value	0.9485***					
	(0.0276)					
Bartik IV		-0.4342***	-0.0034***			
		(0.0180)	(0.0009)			
Inclusive Value		-19.8166***	0.4973***			
		(0.6207)	(0.0187)			
FS Residual (1)				-0.0064	-0.0071	-0.0039
				(0.0055)	(0.0053)	(0.0062)
FS residual (2)				1.0801***	1.0206***	0.1929
				(0.2369)	(0.2367)	(2.1910)
FS Residual^2 (1)					0.0004	0.0008
					(0.0006)	(0.0007)
FS Residual^2 (2)					-1.4221***	-1.4487***
					(0.4533)	(0.5595)
FS Residual (1)*Unempl.						-0.0004
						(0.0003)
FS Residual (2) * IV						-0.0863
						(0.2296)
Observations	40,284	40,280		40,280	40,280	40,280

Note: *p<0.1, **p<0.05, ***p<0.01 Bootstrapped standard errors in parentheses, clusters at the area of origin level. Models at the CAS Ward level. All regressions control for census years fixed effects. Unemployment is defined as the number of unemployed over the sum of workers and unemployed. Population below 16 and above 65, Married/Couples, and People born abroad, are percentage of total population in the CAS Ward. Population with a degree is the percentage of people with a Higher Education degree over population above 16. *Students* is calculated over population aged 16-64.

Table A5. Inflow estimates with British Household Panel Survey and Understanding Society data. Poisson model. Individual level data. Poisson models by reason for moving – Other reasons for moving.

	(1)		(2)	
	Other reasons - stated		**Other – Missing reason**	
Log of distance	-2.2856***	(0.0381)	-1.7029***	(0.0252)
Log of distance ×				
Woman	-0.0647**	(0.0297)	-0.0251	(0.0238)
Married	-0.0415	(0.0430)	0.0246	(0.0448)
Non-white	0.0986	(0.0831)	0.1126*	(0.0611)
Age	-0.0064***	(0.0015)	-0.0049***	(0.0012)
Higher education	0.3216***	(0.0498)	0.2105***	(0.0408)
Mid-level education	0.2170***	(0.0467)	0.2126***	(0.0334)
Social housing	-0.0078	(0.0683)	-0.3239***	(0.0556)
Own house	0.1843***	(0.0472)	-0.1944***	(0.0323)
Working	-0.3016***	(0.0342)	-0.4044***	(0.0294)
Has children	-0.0778***	(0.0258)	-0.1264***	(0.0210)
Is dependent child	-0.0331	(0.1945)	-0.1652*	(0.0965)
Initial unemployment ×				
Woman	-0.0176**	(0.0073)	-0.0119***	(0.0041)
Married	-0.0172	(0.0119)	-0.0495***	(0.0095)
Non-white	0.0125	(0.0102)	0.0793***	(0.0069)
Age	-0.0020***	(0.0003)	-0.0012***	(0.0002)
Higher education	-0.0111	(0.0107)	-0.0082	(0.0085)
Mid-level education	0.0080	(0.0083)	-0.0064	(0.0069)
Social housing	0.0566***	(0.0099)	0.0359***	(0.0084)
Own house	-0.0421***	(0.0110)	-0.0214***	(0.0072)
Working	-0.0490***	(0.0080)	-0.0217***	(0.0061)
Has children	-0.0141**	(0.0059)	-0.0018	(0.0041)
Is dependent child	-0.0435	(0.0303)	-0.0258	(0.0172)
Initial share of white residents ×				
Woman	0.0059***	(0.0010)	0.0015**	(0.0007)
Married	0.0085***	(0.0017)	0.0052***	(0.0014)
Non-white	-0.0119***	(0.0026)	-0.0254***	(0.0019)
Age	0.0004***	(0.0001)	0.0002***	(0.0000)
Higher education	-0.0027	(0.0017)	-0.0047***	(0.0014)
Mid-level education	-0.0019	(0.0015)	-0.0040***	(0.0011)
Social housing	-0.0010	(0.0019)	-0.0028*	(0.0015)
Own house	0.0041***	(0.0016)	0.0055***	(0.0012)
Working	0.0154***	(0.0012)	0.0097***	(0.0007)
Has children	0.0026***	(0.0009)	0.0028***	(0.0007)
Is dependent child	0.0170***	(0.0062)	0.0078**	(0.0034)
N	1,106,114		2,487,543	

Note: *p<0.1, **p<0.05, ***p<0.01 Standard errors are bootstrapped accounting for clusters at the destination area level. Each model accounts for individual*year fixed effects and destination area fixed effects. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis).

Table A6. Outflow estimates with British Household Panel Survey and Understanding Society data. Logit model. Individual level data.

	(1)		(2)	
	Logit – Year FE		Logit – Year + Individual FE	
Area characteristics (own area)				
Unemployment rate 1991	0.0145***	(0.0042)	0.0148	(0.0110)
White share 1991	-0.0005	(0.0042)	-0.0057	(0.0101)
Share of population under 16	-0.0143***	(0.0054)	-0.0030	(0.0140)
Share of population above 65	-0.0093**	(0.0038)	-0.0081	(0.0084)
Share of married/couples	0.0041**	(0.0016)	0.0020	(0.0045)
Share with a degree	0.0115***	(0.0026)	0.0030	(0.0057)
Share of people born abroad	0.0069	(0.0071)	0.0171	(0.0163)
Share of students	-0.0140	(0.0096)	-0.0161	(0.0204)
Other areas characteristics (weighted average)				
Unemployment rate 1991	-0.0499***	(0.0071)	0.0080	(0.0219)
White share 1991	0.0128*	(0.0072)	-0.0021	(0.0217)
Share of population under 16	0.0055	(0.0122)	-0.1028***	(0.0326)
Share of population above 65	0.0066	(0.0075)	-0.0601***	(0.0182)
Share of married/couples	0.0114***	(0.0037)	0.0076	(0.0109)
Share with a degree	-0.0164**	(0.0067)	-0.0279*	(0.0167)
Share of people born abroad	0.0027	(0.0100)	-0.0217	(0.0297)
Share of students	-0.0165	(0.0251)	0.0396	(0.0679)
N	376,367		120,615	

Note: *p<0.1, **p<0.05, ***p<0.01 All models account for clusters in the standard errors estimation at the destination area level. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis). Area level characteristics are obtained as the differences between the levels in one own area and the weighted averaged characteristics in all the other areas. Weights are constructed as individual specific utilities from moving into a specific area using the estimated coefficients from Table 8. All variables are lagged of one period with respect to the outcome. Individual level variables, included in the model, are not displayed for the sake of readability - please refer to Table 12 for the list of the individual level characteristics included.

Table A7. Outflow estimates with British Household Panel Survey and Understanding Society data. Logit model. Individual level data. Inclusive value

	(1)		(2)	
	Logit – Year FE		**Logit – Year + Individual FE**	
Individual characteristics				
Woman	-0.0607***	(0.0129)		
Married	-0.2717***	(0.0238)	-0.2733***	(0.0604)
Non-white	-0.2644***	(0.0416)		
Age	-0.0420***	(0.0007)	-0.0472	(0.0399)
Higher education	0.3652***	(0.0217)	0.4308***	(0.0919)
Mid-level education	0.1585***	(0.0198)	0.3555***	(0.0626)
Social housing	-1.2759***	(0.0353)	-0.8449***	(0.0810)
Own house	-1.4320***	(0.0248)	-0.9270***	(0.0581)
Working	-0.1865***	(0.0191)	-0.1885***	(0.0499)
Number of children	-0.1020***	(0.0109)	-0.1117***	(0.0279)
Is dependent child	-0.7909***	(0.0428)	-0.4525***	(0.0758)
Area characteristics – Area of origin level				
Unemployment rate 1991	-0.0079**	(0.0034)	0.0181*	(0.0097)
White share 1991	0.0038	(0.0029)	-0.0063	(0.0076)
Share of population under 16	-0.0041	(0.0048)	-0.0115	(0.0124)
Share of population above 65	-0.0018	(0.0030)	-0.0141*	(0.0075)
Share of married/couples	0.0077***	(0.0014)	0.0026	(0.0040)
Share with a degree	0.0056**	(0.0024)	0.0021	(0.0055)
Share of people born abroad	0.0040	(0.0038)	0.0063	(0.0108)
Share of students	-0.0133	(0.0084)	-0.0072	(0.0178)
Inclusive Value	0.0547***	(0.0131)	0.1201***	(0.0404)
N	376,367		120,615	

Note: *p<0.1, **p<0.05, ***p<0.01 All models account for clusters in the standard errors estimation at the destination area level. The geographical unit is the CASWard. Initial unemployment and initial share of white residents are from the 1991 Census of Population (source: Nomis). Area level characteristics are obtained as the differences between the levels in one own area and the weighted averaged characteristics in all the other areas. Weights are constructed as individual specific utilities from moving into a specific area using the estimated coefficients from Table 8. All variables are lagged of one period with respect to the outcome

Appendix B – Variables and data construction

1 – Harmonisation of area level information

The analysis we carry on in this paper is at the Census Areas Statistics Wards level. Those areas were created for the Census of Population of 2001[29]. There are 8,850 CAS Wards in England and Wales – they account for a minimum of 100 residents or 40 households - and 1,222 in Scotland – accounting for a minimum of 50 residents and 20 households.

Data for other Census years are provided at different area levels, as the Lower Super Output Areas and Statistical Wards, therefore a harmonisation process had to be done to make local level information comparable.

For Censuses information has been first downloaded at the smallest area level available for England, Wales, and Scotland. We than use National Statistics Postcode Lookup (NSPL) tables to create the share of each geographical area that belongs to each CAS Ward.

NSPL tables relate the current postcodes to a range of administrative, electoral, health, and statistical geographies. For each postcode they also contain the count of Delivery Points (DP), which is the number of addresses and can be used as a proxy for the population present in each postcode. Aggregating these to different area levels we obtain a proxy for the share of the CAS Wards that belongs to each of the other geographies and we use that shares as weights for re-calculating the Census area level characteristics at the CAS Ward level.

For some specifications, for instance to construct our exogenous measure of labour demand, we also use information from 1971 census that uses small geographies – Wards and Electoral Divisions – that are not included in the NSPL tables. In this case we apply a similar procedure using a GIS elaboration of the appropriate area boundaries shapefiles.

[29] For a more detailed description of statistical areas in UK please refer to the Office for National Statistics definitions – some of those available in the National Archives http://webarchive.nationalarchives.gov.uk/.

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1638	Christos Genakos Mario Pagliero	Competition and Pass-Through: Evidence from Isolated Markets
1637	Holger Breinlich Elsa Leromain Dennis Novy Thomas Sampson	Voting With Their Money: Brexit and Outward Investment by UK Firms
1636	Maria Sanchez-Vidal	Retail Shocks and City Structure
1635	Felipe Carozzi Sefi Roth	Dirty Density: Air Quality and the Density of American Cities
1634	Nicholas Bloom John Van Reenen Heidi Williams	A Toolkit of Policies to Promote Innovation
1633	Stephan E. Maurer Ferdinand Rauch	Economic Geography Aspects of the Panama Canal
1632	Nikhil Datta	Willing to Pay for Security: A Discrete Choice Experiment to Analyse Labour Supply Preferences
1631	Gabriel M. Ahlfeldt Volker Nitsch Nicolai Wendland	Ease Versus Noise: Long-Run Changes in the Value of Transport (Dis)amenities
1630	Grace Lordan Alistair McGuire	Widening the High School Curriculum to Include Soft Skill Training: Impacts on Health, Behaviour, Emotional Wellbeing and Occupational Aspirations
1629	Per-Anders Edin Tiernan Evans Georg Graetz Sofia Hernnäs Guy Michaels	Individual Consequences of Occupational Decline

1628	Pawel Bukowski Filip Novokmet	Between Communism and Capitalism: Long-Term Inequality in Poland, 1892-2015
1627	Thomas Sampson	Technology Gaps, Trade and Income
1626	Andrea Ichino Martin Olsson Barbara Petrongolo Peter Skogman Thoursie	Economic Incentives, Home Production and Gender Identity Norms
1625	Richard Murphy	Why Unions Survive: Understanding How Unions Overcome the Free-Rider Problem
1624	Natalie Chen Wanyu Chung Dennis Novy	Vehicle Currency Pricing and Exchange Rate Pass-Through
1623	Michael Amior Alan Manning	Commuting, Migration and Local Joblessness
1622	Rui Costa Swati Dhingra Stephen Machin	Trade and Worker Deskilling
1621	Jan-Emmanuel De Neve Clement Imbert Johannes Spinnewijn Teodora Tsankova, Maarten Luts	How to Improve Tax Compliance? Evidence from Population-wide Experiments in Belgium
1620	David S. Jacks Dennis Novy	Trade Blocs and Trade Wars during the Interwar Period
1619	Giulia Faggio Olmo Silva William C. Strange	Tales of the City: What Do Agglomeration Cases Tell Us About Agglomeration in General?

The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
Website: http://cep.lse.ac.uk Twitter: @CEP_LSE