CENTRE for ECONOMIC
PERFORMANCE

CEP Discussion Paper No 1623

June 2019

Commuting, Migration and Local Joblessness

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OF ECONOMICS AND
POLITICAL SCIENCE

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Abstract
Britain suffers from persistent spatial disparities in employment rates. This paper develops an integrated framework for analyzing two forces expected to equalize economic opportunity across areas: commuting and migration. Our framework is applicable to any level of spatial aggregation, and we use it to assess their contribution to labor market adjustment across British wards (or neighborhoods). Commuting offers only limited insurance against local shocks, because commutes are typically short and shocks are heavily correlated spatially. Analogously, migration fails to fully equalize opportunity because of strong temporal correlation in local demand shocks.

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

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1 Introduction

Britain suffers from very persistent spatial disparities in joblessness. Figure 1 compares working-aged (16-64) employment-population ratios (from here on, "employment rates") in 1981 and 2011, across the 50 largest British Travel to Work Areas (TTWAs, approximately equivalent to Commuting Zones in the US): the correlation is 0.54.[1] As we show below, this persistence cannot be explained by observable variation in local demographic composition: rather, it appears to reflect disparities in economic opportunity. While local shocks to labor demand can certainly cause short-run differences in economic opportunity to emerge, it is less clear why they should persist for so long (as in Figure 1). In principle, they should be eliminated through movements of labor, either migration or commuting, from areas of high to low joblessness.

Most existing studies of adjustment to local demand shocks have focused on the migration channel (see e.g. Blanchard and Katz, 1992; Eichengreen, 1993; Decressin and Fatás, 1995; Obstfeld and Peri, 1998; Beyer and Smets, 2015; Dao, Furceri and Loungani, 2017; Amior and Manning, 2018). A common explanation for Britain's persistent regional inequalities is low internal migration rates. However, Figure 2 shows that areas with high joblessness in 1981 experienced much lower population growth over the next 30 years. The size of the response is similar to that documented in the US by Amior and Manning (2018). Just as in the US, we argue that these large population responses are insufficient to eliminate the spatial disparities because of persistence in the demand shocks themselves: those areas which shed jobs in the 1960s and 1970s continue to shed them today. Figure 3 shows a strong positive correlation between local employment growth over 1971-1991 and 1991-2001. The most plausible explanation for these disparities is the spatially uneven impact of the decline of manufacturing.

Commuting is another mechanism which can, in principle, equalize economic opportunity across areas - and may be important in a small, densely populated country like Britain. Residents of areas suffering contractions of demand may be able to commute elsewhere without moving away.[2] The response of commuting to labor demand shocks is much less studied than migration, though there are important exceptions. Manning and Petrongolo (2017) show how changes in commuting patterns can cause local shocks to ripple through space, in a search-theoretic environment with fixed local populations. And using a calibrated equilibrium model, Monte, Redding and Rossi-Hansberg (2018) show how the elasticity of local labor supply depends on both population and commuting responses - with the latter varying with local commuting access. But in contrast to Monte, Redding and Rossi-Hansberg (2018), our focus is on local disparities in welfare (away from the steady-state) rather than aggregate welfare - and the contribution of migration and commuting to redressing these

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[1] In popular discussion, these differences are often described as the "North-South divide"; and indeed, Figure 1 shows employment rates in Northern TTWAs are almost always lower than in Southern TTWAs. See Blackaby and Manning (1990) for the North-South divide in earnings, Henley (2005) for output, and Dorling (2010) for a wider range of variables.

[2] Green, Morissette and Sand (2017) argue further that the mere option to commute (even if not exercised) can strengthen workers' bargaining power and affect local wages.

disparities. We also estimate the commuting responses empirically: apart from a "labor market accounting" exercise[3] from Beatty, Fothergill and Powell (2007), we are not aware of another study which does.

In this paper, we develop an integrated framework for analyzing and estimating both the commuting and migration responses to local demand shocks, and we use it to provide an account of why local joblessness is so persistent in Britain. One attractive feature of our approach is that it can be applied at any level of spatial aggregation, no matter how small. Our main conclusion is that while both commuting and migration do respond to demand shocks, they play a limited role in equalizing opportunity. Just as large temporal correlation in local demand shocks limits the effectiveness of migration in eliminating disparities (the central point of Amior and Manning, 2018), so too large spatial correlation limits the effectiveness of commuting. Given that most workers only commute over short distances, commuting offers little insurance against local shocks.

Our study contributes to a broader literature on spatial mismatch between jobseekers and employers: see e.g. Kain (1968); Hellerstein, Neumark and McInerney (2008); Holzer (1991); Ihlanfeldt and Sjoquist (1998); Şahin et al. (2014); Marinescu and Rathelot (2018). An important strand of work has emphasized the role of search frictions in determining commuting patterns (e.g. Manning, 2003*b*; Van Ommeren, Rietveld and Nijkamp, 1997, 1999) and spatial inefficiencies in equilibrium (Coulson, Laing and Wang, 2001; Wasmer and Zenou, 2002; Rupert and Wasmer, 2012; Guglielminetti et al., 2015). Our focus here is on the role of sluggish adjustment in driving mismatch, away from the steady-state. Our estimates also offer some insights on the possible contributions of infrastructure investments to local adjustment. This builds on a large literature which explores the impact of such investments on commuting patterns: see e.g. Baum-Snow (2010), Duranton and Turner (2012), Gibbons et al. (2019) and Heuermann and Schmieder (2018).

The plan of the paper is as follows. Section 2 describes our data and offers estimates of the temporal and spatial correlation in employment rates. We use decadal British census observations between 1971 and 2011, and we study two levels of spatial aggregation: wards (equivalent to neighborhoods) and Travel-To-Work-Areas (TTWAs). The latter are the British equivalent of American "Commuting Zones" and are constructed to reflect, as far as possible, self-contained labor markets. British data on population, employment and commuting flows are ideally suited to our application: they are available for remarkably

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[3]In this analysis, Beatty, Fothergill and Powell decomposes changes in local employment in British coal-fields into contributions from migratory and commuting flows.

detailed geographies and going back several decades. This allows us to study adjustment at the very local level and over long horizons.

In Section 3, we derive a crucial result which underpins our model: the local welfare of residents in an area can be written as a function of the local employment rate and the utility of being unemployed. This is an extension of the "sufficient statistic" result of Amior and Manning (2018) to the case where individuals can work outside their area of residence, i.e. commute. This generalization can be applied at any level of spatial aggregation and also allows us to "decouple" the analysis of migration and commuting. Given the spatial distribution of population and labor demand at a given point in time, individuals in each area choose where to commute for work - or whether to work at all. These choices determine the local employment rate, which summarizes local welfare and therefore drives workers' migration decisions.

We describe our model of commuting and local labor markets in Section 4, for a fixed spatial distribution of population. We show how panel data on commuting flows can be decomposed into (i) time-invariant costs of commuting between all area pairs and (ii) time-varying area-specific fixed effects. The latter can be interpreted as the value of working in a given area, e.g. its wage. We provide estimates of how commuting responds to local shocks. We then use these estimates to compute the value of work for residents of every area, which account for the commuting opportunities. In line with the predictions of the theory, we show that the return to work estimated from commuting data alone is a useful predictor of the local employment rate.

In Section 5, we set out and estimate a model for migration. Allowing for sluggish adjustment of local population[4], Amior and Manning (2018) show how the sufficient statistic result gives rise to an error correction mechanism (ECM): local population growth depends on contemporaneous employment growth and the lagged employment rate, which represents initial local differentials in welfare. The model fits the British data well. As predicted by our sufficient statistic result, our estimates of the ECM are similar for both ward and TTWA-level data. We also find substantial population responses across wards *within* TTWAs - which is consistent with the limited insurance offered by commuting. In our preferred ward-level estimates, the elasticity of population to contemporaneous (decadal) employment growth is 0.61, and the elasticity to the initial local employment rate is 0.42. This implies a large but incomplete population adjustment over ten years: it corrects for about half the initial

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[4]See also Vermeulen and Ommeren (2009), Desmet, Nagy and Rossi-Hansberg (2018) and Jaeger, Ruist and Stuhler (2018) for analyses which account for sluggish population adjustment.

deviation in the local employment rate. These estimates point to a more sluggish migratory response than earlier studies (such as Blanchard and Katz, 1992, and Decressin and Fatás, 1995). However, they are not significantly different to our US estimates based on the same empirical model.

Section 6 analyzes the effectiveness of commuting and migration in reducing spatial inequalities. A version of Moran's I emerges naturally from the commuting model as a measure of spatial correlation in shocks, and we estimate this correlation to be substantial. The impact of demand shocks is very local, essentially because commutes are short. Given the tight spatial correlation of shocks and the short commutes, commuting can only offer limited insurance against local shocks (at least on average). Analogously, the effectiveness of migration in reducing spatial inequalities is limited by the high temporal correlation in shocks. We also assess the relative effectiveness of reducing commuting and migration costs in eliminating local differentials in joblessness: migration plays the dominant role.

Though the purpose of our paper is to understand the persistence of local joblessness in the UK, we make a number of more general contributions:

1. A generalization of Amior and Manning's (2018) result that the employment rate in an area can serve as an (easily computed) sufficient statistic for local economic opportunity - to the case where workers can work outside their area of residence.

2. A model of the commuting decision: i.e. the choice of area of work, conditional on area residence. The utility of the various options depends on wage offered and commuting cost. We present evidence that commuting patterns change in response to local demand shocks.

3. A model of the determination of the employment rate among residents of a given area, as a function of economic conditions in surrounding areas.

4. A model of migration between areas, which depends on local differentials in employment rates.

2   Data

2.1   Geography

We study two levels of spatial aggregation: (1) wards, which can be interpreted as "neighborhoods", and (2) TTWAs, which are constructed by the Office for National Statistics to

represent self-contained labor markets based on data on commuting flows.[5]. The official boundaries of both wards and TTWAs have changed over time: we construct 9,975 consistent wards (covering the entirety of England, Scotland and Wales), based on the 2001 census Standard Table definitions, and 232 consistent TTWAs based on the 2001 census scheme. See Appendix A for further details.

We take local population and employment counts (for individuals aged 16-64) from the published small area statistics of the 1971, 1981, 1991, 2001 and 2011 censuses.[6] For our commuting analysis, we rely on the British census' Special Workplace Statistics, which record commuting flows between every pair of wards. This data is available for census years between 1981 and 2011 inclusive. See Appendix A for further details.

Table 1 presents various statistics on the distribution of wards and TTWAs. The median ward has a population of 4,000 and the median TTWA 120,000. 21 percent of employed individuals work in their ward of residence and 81 percent in their TTWA of residence. We show in Figure 5 below that commutes are typically very short: 50 percent of workers commute less than 5km and 90 percent under 30km. Returning to Table 1, the distribution of employment rates is similar for both wards and TTWAs and changes little over the sample period.

British TTWAs are comparable to the US Commuting Zones (CZs) developed by Tolbert and Sizer (1996) and popularized by Autor and Dorn (2013) and Autor, Dorn and Hanson (2013). Table 1 offers equivalent statistics for the 722 CZs of the Continental US, over the same period. British TTWAs and American CZs are similar in terms of population; but TTWAs are significantly smaller in land area (and so, more densely populated), and there is more commuting between them.

2.2   Temporal persistence of local employment rates

Figure 1 suggested a high level of persistence in employment rates: this is documented more formally here. Table 2 presents autocorrelation functions (ACFs) of the time-demeaned log local employment rate over four decadal lags, based on the full panel between 1971 and 2011

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[5]See   *http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/other/travel-to-work-areas/index.html*.

[6]Unfortunately, the small area statistics of the 1961 census have not yet been digitized: see *http://britishlibrary.typepad.co.uk/socialscience/2013/01/census-statistics-and-resources.html*.

of both wards and TTWAs. The first row estimates a ward-level autocorrelation of 0.76 at the first decadal lag and 0.25 at the fourth, and the numbers are very similar for TTWAs. Rows 2 and 3 show the persistence is higher for men than women at longer lags: 0.5 for men by the fourth lag, compared to zero for women.[7]

One concern is that the ACFs may merely reflect persistence in local demographic composition. Microdata census samples are only available with coarser geographical identifiers. Using this, we construct 118 geographical units (which we denote "microdata TTWAs"), which roughly correspond to groups of TTWAs (see Appendix A.5). As the fifth row shows, the ACF of the employment rate for these areas looks similar to that of wards and TTWAs. We then adjust local employment rates for demographic composition: for each census year and separately for men and women, we estimate a probit model of employment on a set of demographic characteristics[8] and a full set of geographical identifiers. And based on the probit estimates, we predict the mean employment rate in each area for a distribution of demographic characteristics identical to the full national sample. Row 6 shows this makes almost no difference to the ACF, consistent with our findings for the US (Amior and Manning, 2018).

One might be concerned about the role played by unobservables, though the fact that observable characteristics make little difference to the estimated persistence offers some reassurance. One way of controlling for time-invariant unobserved factors is to condition on area (ward or TTWA) fixed effects. Given the panel is short, using fixed effects introduces an artificial negative correlation between current and lagged employment rates: and hence the implausible negative autocorrelations in row 7. Amior and Manning (2018) propose a method to correct this bias, though this requires one identifying assumption: our approach is to fix the ratio π of the fourth to third autocorrelation. In rows 8-10, we report results for $\pi = 0.9$, $\pi = 0.5$ and $\pi = 0$. The ACFs for the positive πs look similar to row 1, and we even see large persistence at the early lags for the extreme $\pi = 0$ case.

To summarize, there appears to be substantial local persistence in employment rates, which cannot be explained by local demographic composition or unobserved area effects.

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[7]Women were entering the labor force in greater numbers during the sample period, so the change in their employment rates presumably reflect supply as well as demand factors. Indeed, when we estimate the employment rate ACF using labor force participants only (in row 4), we again see large numbers at the higher lags - similar to men.

[8]Specifically, a quadratic in age, an indicator for college education (interacted with the age quadratic), and a foreign-born indicator (interacted with all previously-mentioned variables).

The observed differences in employment rates appear to reflect real differences in economic opportunity.

2.3 Spatial correlation of local employment rates

Employment rates have a high degree of spatial, as well as temporal, correlation: this will turn out to be important for how effective commuting is in offering insurance against local demand shocks. To illustrate the extent of spatial correlation, Figure 4 presents estimates of the "incremental" spatial autocorrelation. For distance d, this is equal to Moran's I (Moran, 1950) with weights of 1 applied to areas within distance d and 0 to all others. Details of the implementation can be found in Appendix A.6. Figure 4 shows that Moran's I is 0.6 within the first kilometer, declines to 0.4 by the fifth kilometer, and only reaches 0.2 by the 50th. As noted above (and see also Figure 5 below), most commutes are relatively short, so this implies high levels of spatial autocorrelation over the distances that most people commute.

2.4 Instrumental variables

As explained in more detail later, credible identification of our estimating equations requires instruments, one for labor demand (which excludes supply shocks) and one for labor supply (which excludes demand). In keeping with much of the literature, we rely on the industry shift-share variables X_{rt} originally proposed by Bartik (1991) as a demand-side instrument. This predicts local employment growth in each area a, based on the initial industrial composition and assuming that employment in each industry i grows at the national rate:

$$\Delta log X_{at} = \sum_i s_{at-1}^i \left[\log N_{i(-a)t} - \log N_{i(-a)t-1} \right] \tag{1}$$

where s_{at-1}^i is the share of workers in area a at time $t-1$ employed in industry i. The term in square brackets is the growth of employment nationally in industry i, excluding area a. This modification to standard practice was proposed by Autor and Duggan (2003) and Goldsmith-Pinkham, Sorkin and Swift (2018) to address concerns about endogeneity to local employment counts. We construct this instrument using firm surveys and use a fine industrial disaggregation (212 different industries): see Appendix A for further details. This

employment measure is based on *workplace* rather than *residen*ce: in the context of cross-area commuting, this is the appropriate measures of changes in local economic opportunity.

For our labor supply instrument, we exploit the contribution of immigration to local population growth. As is well known, new foreign migrants are often attracted to areas with large co-patriot communities[9]. In this spirit, we implement the common migrant shift-share instrument (popularized by Altonji and Card, 1991, and Card, 2001) which predicts the contribution of foreign migration to local population growth:

$$M_{at} = \frac{\sum_o s^o_{at-1} \Delta M_{o(-a)t}}{L_{at-1}} \tag{2}$$

where s^o_{at-1} is the share of migrants of origin o who live in area a at time $t-1$; and $\Delta M_{o(-a)t}$ is the change in the national stock of origin o migrants between $t-1$ and t, excluding area a (for the same reasons as above). The numerator of (2) then predicts the inflow of all migrants to area r; and this is scaled by L_{at-1}, the initial population of area r. We construct this Altonji-Card shift-share using small area statistics from the census data. Population is decomposed by country (or country group) of birth, though these country categories vary by census cross-section. For each pair of census years, we use the greatest possible origin country detail: this consists of between 9 and 23 origin categories, depending on census year. See Appendix A for further details.

3   Model overview

We now present the analytical framework we use to model commuting and migration.

3.1   Utility

Individuals choose where to live (though migratory adjustment is sluggish); and conditional on their residence, they choose (whether and) where to work. There are A areas, and individuals can potentially live and/or work in any of them. Denote the area of residential location by a, $a = 1, .., A$ and the area of work by b, $b = 1, .., A$. For an individual living in a and working in b, utility is:

$$U_{ab} = V_{ab} + \varepsilon_{ab} \tag{3}$$

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[9]For example, because of job networks (Munshi, 2003) or cultural amenities (Gonzalez, 1998).

where V_{ab} measures the attractiveness of working in b for a resident of a, and ε_{ab} is an idiosyncratic utility shifter. To keep notation to a minimum, we characterize the option $b = 0$ as non-employment. Given their current residence, individuals choose the workplace that offers the highest utility. For the residential decision, we assume the utility from living in different areas affects the propensity to move between them, but that this process takes time. This different treatment of the commuting and migration decision seems appropriate if it is easier to change workplace than residence.[10]

As is usual in such models, it is convenient to work backwards, i.e. start with treating the residential decision as fixed, and analyze the work/commute decision. This provides a measure of the welfare from living in different areas, which we use to model the choice of where to live. Let N_a denote total employment of the residents of a, and L_a total working-age population. The employment rate is then $\frac{N_a}{L_a}$.

3.2 "Sufficient statistic" result

This section shows that, under some conditions, the utility of living in an area can be written as a function of the local employment rate and out-of-work utility. We make three assumptions:

1. GEV assumption. The idiosyncratic terms in (3) follow a generalized extreme value distribution:

$$F\left(\epsilon_{a.}\right) = e^{-G\left(e^{-\varepsilon_{a0}}, e^{-\varepsilon_{a1}}, .., e^{-\varepsilon_{aA}}\right)} \tag{4}$$

for some function $G\left(.\right)$, monotonic and homogeneous of degree 1 in its arguments. This is the generalized extreme value model of McFadden (1978).

2. Limited IIA assumption. For an individual living in a, we assume that the relative probability of choosing employment in area b compared to b' does not depend on the non-employment utility, V_{a0}. This is a limited form of "independence of irrelevant alternatives" (IIA) which pertains only to the non-employment option, $b = 0$.

3. Elastic labor supply. An increase in the utility from working in any area leads to an increase in the employment rate. Much of the literature that uses Rosen-Roback models assumes an inelastic labor supply curve (or "wage curve", if one prefers a non-competitive model), but there is plenty of evidence: see e.g. the wage curve literature of Blanchflower and Oswald (1994).

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[10]For example, Manning (2003a) finds that 20 percent of workers have less than one year of job tenure, compared to 10 percent with under a year of residential tenure.

Together, these assumptions yield the "sufficient statistic" result:

Proposition. *Given the GEV, Limited IIA and Elastic Labor Supply assumptions, the expected utility of living in area a can be written as:*

$$\overline{U}_a = E\left(\max_b U_{ab}\right) = V_{a0} + \Psi\left(\frac{N_a}{L_a}\right) \tag{5}$$

for some function Ψ of the local employment rate $\frac{N_a}{L_a}$.

Proof. See Appendix B. □

This can be interpreted as an application of the "conditional choice probability" result of Hotz and Miller (1993). The Limited IIA assumption implies that employment and non-employment are in separate choice nests. Assuming an elastic labor supply, the probability of being in employment (which is the employment rate) therefore depends on the difference between the inclusive value of being in employment and the value of non-employment. And a "Hotz-Miller inversion" then allows us to write the difference in utility as a function of the employment rate. The Limited IIA is satisfied by most of the commonly used functional forms in the discrete choice literature, for example a simple multinomial logit or a more complicated model based on the Frechet distribution, or alternatively a nested logit specification in which one of the nests is non-employment.

The sufficient statistic result allows us to reduce the expected utility of residing in an area to just two dimensions: the local out-of-work utility and the local employment rate. The employment rate summarizes the value of all the (potentially very many) commuting options: this is very helpful when, as here, there are a large number of areas. Intuitively, to the extent that employment in some area becomes more attractive, this will materialize in a larger overall probability of working. This is an extension of the "sufficient statistic" result of Amior and Manning (2018) to the case where people can live in one area and work in another.

We now turn to the estimation of our model. This proceeds recursively. Section 4 considers the commuting decision conditional on living in an area and being employed, and then derives the employment rate conditional on the commuting choices - for a fixed spatial distribution of population. And Section 5 then analyzes the residential location decision, conditional on the employment rate.

4   Labor market model for fixed local populations

In this section, we set out and estimate a model of local labor markets for a fixed spatial distribution of population. We begin with a model of commuting; and we then consider the determination of local wages, and ultimately, the employment rates of local residents - our sufficient statistic for local economic opportunity.

4.1   Commuting model

We write the non-idiosyncratic component of utility (3) from living in a and working in b at time t as:

$$V_{abt} = \phi_{0at} + d_{ab} + \phi \left(\log W_{bt} - \log Q_{at} \right) \tag{6}$$

where ϕ_{0at} is the amenity value of living in a, and d_{ab} is a time-invariant origin-destination fixed effect which represents the commuting cost: this may be a simple function of the distance between a and b, though it could also be influenced by transport networks. W_{bt} is the attractiveness of jobs offered by employers in b at time t: the notation reflects the relevance of the wage, though other factors may be important. And Q_{at} is the consumer price index for residents of a at time t. The price index is determined by:

$$\log Q_{at} = \zeta \log Q_{at}^{h} + (1 - \zeta) \log Q_t \tag{7}$$

where Q_t is the price of the (single) traded good, Q_{at}^{h} is the local price of housing, and ζ can be interpreted as the share of total consumer expenditure going to housing. To derive an estimable commuting model, we assume the idiosyncratic error term ε in (3), conditional on working, has a simple extreme value form. Conditional on working, this leads to a multinomial logit structure for the probability of commuting from a to b at time t:

$$\omega_{abt} = \frac{N_{abt}}{N_{at}} = \frac{e^{d_{ab} + \phi \log W_{bt}}}{\sum_i \left(e^{d_{ai} + \phi \log W_{it}} \right)} \tag{8}$$

where N_{abt} is the number of workers commuting from a to b. Note the local consumer price index and the residential amenity drop out from this expression: while they affect the utility of living in a, they do not affect the relative attractiveness of working in different areas - conditional on residence.

12

4.2 Estimating the commuting model

We use data on commuting flows to estimate (8), treating the "wage" W_{bt} as an unobserved destination-time fixed effect that is a parameter to be estimated. From (8), a doubling of $\log W_{bt}$ or d_{ab} leaves the commuting probabilities unchanged: as a result, the origin-destination fixed effects, d_{ab}, and destination-time fixed effects, W_{bt}, can only be identified up to some normalization. To clarify what can be identified, define:

$$D_{ab} = \frac{e^{d_{ab}+\phi \log W_{b1}}}{\sum_i \left(e^{d_{ai}+\phi \log W_{i1}} \right)} \tag{9}$$

where $t = 1$ is the first period and:

$$Z_{bt} = \frac{e^{\phi(\log W_{bt}-\log W_{b1})}}{\sum_i e^{\phi(\log W_{it}-\log W_{i1})}} \tag{10}$$

By construction, D_{ab} sums to one for all a and Z_{bt} to one for all t. We normalize Z_{b1} to be identical for all b. D_{ab} and Z_{bt} then represent the most that can be identified from data on commuting patterns (though other normalizations are possible) . Using (9) and (10), (8) can be written as:

$$\omega_{abt} = \frac{D_{ab}Z_{bt}}{\sum_i D_{ai}Z_{it}} \tag{11}$$

We estimate this by maximum likelihood, the details of which are in Appendix C. Our estimates of the D_{ab} and Z_{bt} offer one way of decomposing the commuting flow matrices into origin-destination fixed effects and time-varying-destination fixed effects. We now model these two components separately.

4.3 Modeling D_{ab}

From (9), D_{ab} is decreasing in the commuting cost d_{ab} between origin and destination. We parameterize d_{ab} as a quadratic in the log of distance[11] $dist_{ab}$ between areas a and b:

$$d_{ab} = \gamma_0 + \gamma_1 \log dist_{ab} + \gamma_2 \left(\log dist_{ab} \right)^2 \tag{12}$$

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[11]In line with Manning and Petrongolo (2017), we assume the distance of within-ward commutes is equal to the average distance between two random points in a circle with the same area as the ward. We measure distances between wards according to population-weighted centroids, based on population counts within 218,000 very local "output area" units in 2011: see Appendix A.1 for further details on geographical units.

The formula in (9) has multinomial logit form. Direct estimation is infeasible because of the number of options in our application, so we exploit the well-known equivalence between the multinomial logit model and a Poisson model when an origin fixed effect is included (see, for example, Baker, 1994). Based on the definition of D_{ab} in (9), a destination fixed effect (the term $\log W_{b1}$) is also required, so we need a Poisson model with two-way fixed effects. To estimate this model, we use the iterative procedure suggested by Aitkin and Francis (1992) and Guimaraes (2004): we use a given set of origin and destination fixed effects as offsets in a standard Poisson model and estimate the coefficients on the regressors of interest. Then, using these estimates, we re-estimate the fixed effects and repeat until convergence. This process can be slow, but it does eventually converge without the need to invert matrices which in our case would contain approximately 400m elements. This process does not produce estimates of standard errors, but we follow Guimaraes (2004) and use a likelihood ratio test to produce t-ratios. The results are reported in Table 3.

As one would expect, more distant jobs are estimated to be less attractive. The coefficients in column 1 should be interpreted in the following way: ceteris paribus, a job 5km away draws only about 8 percent of the flows of a job 1km away.[12] That is, given residence, labor markets are very local. This is in line with the evidence of Manning and Petrongolo (2017). Although the definition of D_{ab} in (9) and the Poisson version of the multinomial logit model strongly suggests that both fixed effects are needed, estimation of this model is very time-consuming, and one might wonder whether simpler estimation procedures produce similar results. Columns 2-4 report estimates of Poisson models with different combinations of origin and destination fixed effects, columns 5-6 report the results of a log-linear regression (which drops the zeroes) with and without fixed effects, and column 7 is estimated by non-linear least squares without fixed effects. The estimates from the Poisson models are quite similar irrespective of the fixed effects included, but the log-linear and non-linear least squares model are very different.[13]

4.4 Modeling wages

This section develops a simple model of wages that has a number of elements: labor supply, production and a housing market. We offer a simple competitive model, where local wages

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[12]More specifically: $\frac{1.13 \times 5 + 0.23 \times 5^2}{1.13 \times 1 + 0.23 \times 1^2} = 8.38$.

[13]This is in line with the findings on the gravity model in international trade.

are determined by the realized supply of labor from the full set of locations. But see Green, Morissette and Sand (2017) for a bargaining model where the mere option to commute (even if not exercised) can affect local wages.

Labor supply

From the logit assumption (8) which underpins the commuting model, one can derive the inclusive value of working while living in area a at time t:

$$IV_{at}^n = \log \sum_b e^{d_{ab} + \phi \log W_{bt}} \tag{13}$$

This can be interpreted as a summary measure of the value of working, expressed in nominal terms. Accounting for local prices, the real value is $IV_{at}^n - \phi Q_{at}$. The Limited IIA assumption implies that the probability of working, $\frac{N_{at}}{L_{at}}$, depends on the difference between the local values of working and not working. For simplicity, suppose the value of not working is spatially invariant is not affected by local prices. Using a log-linear approximation, together with (7), the employment rate can then be summarized as[14]:

$$\log \frac{N_{at}}{L_{at}} = \psi \left(IV_{at}^n - \phi \zeta \log Q_{at}^h \right) + TimeEffects + AreaEffects \tag{14}$$

Note that the time effects will include some endogenous variables. However, our aim here is not to solve the model as a whole, but rather to develop an estimable model in which aggregate effects can be captured by time effects.

Given the assumptions on commuting in (8), the commuter flow from a to b can then be written as:

$$N_{abt} = \omega_{abt} \cdot \frac{N_{at}}{L_{at}} \cdot L_{at} = \left(e^{d_{ab} + \phi \log W_{bt}} \right) \left(e^{IV_{at}^n} \right)^{-(1-\psi)} \left(Q_{at}^h \right)^{-\psi \phi \zeta} L_{at} \tag{15}$$

where we have dropped multiplicative time effects in the interests of simplicity. Let N_{bt}^w be the total supply of labor to area b:

$$N_{bt}^w = \sum_a N_{abt} \tag{16}$$

Note this is employment by *workplace*, in contrast to N_{bt} which is employment by *residence*.

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[14]In general, this will not be a log-linear equation, but we use this approximation in deriving an estimating equation. So it is easier to impose it from the start.

Labor demand and wages

Suppose there are constant returns to scale in production within individual firms: output in area b, Y_b, is given by $Y_b = \widetilde{A}_b N_b^{w\,15}$. However, returns may be non-constant at the local level due to a production externality: we assume $\widetilde{A}_b = A_b \left(N_b^w \right)^\varphi$, where a positive φ indicates increasing returns (i.e. an agglomeration externality) and vice versa. If we assume that prices are equal to marginal costs (a mark-up would make no difference), we have:

$$\log W_{bt} = \log A_{bt} + \varphi \log N_{bt}^w + \log P_{bt} \tag{17}$$

where P_{bt} is the local producer price at time t. We assume that firms in area b face a downward-sloping demand curve for their products with price elasticity θ:

$$\log Y_{bt} = \log A_{bt} + (1 + \varphi) \log N_{bt}^w = -\theta \log P_{bt} + \log X_{bt} + TimeEffects + AreaEffects \tag{18}$$

where X_{bt} is a demand shock. This product demand equation can be derived from an underlying model of CES preferences, where the aggregate price index is included in the time effects. Because we assume all goods are tradable, the local level of income does not affect the product demand curve.[16]

Housing market

We assume that the log housing supply in area a, denoted by $\log H_{at}^s$, is given by:

$$\log H_{at}^s = \epsilon^{hs} \log Q_{at}^h + TimeEffects + AreaEffects \tag{19}$$

We assume that housing demand, $\log H_{at}^d$, is proportional to the size of the local population, L_{at}, and increasing in local per capita income. Per capita income in turn depends on the local employment rate $\frac{N_{at}}{L_{at}}$ and local earnings for those in employment, where the latter can be represented by the inclusive value IV_{at}^n. Writing a log linear approximation, and accounting for the demand response to local prices Q_{at}^h, we have that:

$$\log H_{at}^d = -\epsilon^{hd} \log Q_{at}^h + \log L_{at} + \gamma_1 \log \frac{N_{at}}{L_{at}} + \gamma_2 IV_{at}^n + TimeEffects \tag{20}$$

---

[15]Constant returns is assumed for simplicity: the same equations would result from assuming non-constant returns.

[16]This assumption greatly simplifies the model; but as we note in footnote 18 below, it will not affect the empirical specification.

Equilibrium

The endogenous variables are local wages, employment of each area's residents in every other area, housing stock and prices, all of which can be derived from equations (15)-(20). Appendix D derives a linearized approximation of the response of the vector of log wages $\Delta \log \mathbf{W}_t$ (across all areas) to the vector of labor demand shocks $\Delta \log \mathbf{X}_t$ (driven by changing preferences or productivity) and to the vector of labor supply shocks, as given by the vector of log working-age populations in each area, $\Delta \log \mathbf{L}_t$.

Appendix D shows the change in wages can be approximated by:

$$\Delta \log \mathbf{W_t} \approx \alpha_2 \left[\mathbf{I} + \alpha_1 \mathbf{\Omega^{nw}} \mathbf{\Omega^{nr}} \right] \Delta \log \mathbf{X_t} - \alpha_3 \left[\mathbf{I} + \alpha_1 \mathbf{\Omega^{nw}} \mathbf{\Omega^{nr}} \right] \mathbf{\Omega^{nw}} \Delta \log \mathbf{L_t} + TimeEffects \tag{21}$$

where $\mathbf{\Omega^{nw}}$ is a non-negative weight matrix whose rows sum to one, and the jth column of the ith row represents the share of area i employees who reside in area j.[17] Similarly, $\mathbf{\Omega^{nr}}$ is a non-negative weight matrix whose rows sum to one, and the jth column of the ith row represents the share of (employed) area i residents who work in area j. Appendix D shows that the parameters $(\alpha_1, \alpha_2, \alpha_3)$ are complicated non-linear functions of the underlying parameters of the model which cannot be separately identified in estimation. The response of wages to demand and population shocks can, however, be identified.

(21) implies that local wages in area b are increasing in the own-ward demand shock, $\Delta \log X_{bt}$, as one would expect: more labor must be recruited to produce the extra output demanded (see the term in square brackets). Local wages are also increasing in the demand shocks in surrounding areas: a positive demand shock attracts labor from neighboring areas, causing wages to rise in these areas. The Markov matrix $\mathbf{\Omega^{nw}} \mathbf{\Omega^{nr}}$ measures the interaction with other wards: it is a double-convolution because workers consider working in a range of areas (as given by $\mathbf{\Omega^{nw}}$), whose local firms themselves employ workers from multiple origins (as given by $\mathbf{\Omega^{nr}}$).

The impact of changes in population, $\Delta \log \mathbf{L_t}$, is different. First, there is no special own-ward effect of population growth as shown by the fact there is no identity matrix term. The impact on wages in some area b depends on a weighted average of local population changes, with the weights equal to the shares of different locations in the labor supply to area b. In the model developed here, a larger weighted labor supply necessarily depresses wages, because the larger output reduces prices and the marginal revenue product of labor.[18] There is also

---

[17]The derivation of (21) in Appendix D comes from a first-order approximation to the interactions between areas. Higher-order approximations would lead to come complicated and higher-order convolutions.

[18]This comes from the assumption that all goods produced by labor are traded. If there are non-traded

a double-convolution because changes in local population affect the labor supply to other wards, which affects the wages offered there, and which in turn affect the wages offered here.

Modeling $\Delta \log Z_{bt}$ and local wages

Now consider how (21) can be estimated. We proxy $\Delta \log \mathbf{X_t}$ with the Bartik shocks described earlier. $\Delta \log \mathbf{L}_t$ is measured by the change in the log of working-age population. Wages are not observed directly in our data, as the UK census has no earnings information. But, from (10), we have that $\Delta \log Z_{bt} = \phi \Delta \log W_{bt}$ (plus time effects); so the model for wages in (21) can be interpreted as a model for $\Delta \log Z_{bt}$.

In Table 4, we offer estimates of (21), but replacing the dependent variable with $\Delta \log Z_{bt}$. On the right hand side, we include two Bartik variables (the own-ward shock and the double convolution) and two local population shocks (the second, again, with a double convolution) - in accordance with (21). To construct the convolutions, we require the $\mathbf{\Omega^{nw}}$ and $\mathbf{\Omega^{nr}}$ matrices. We compute these using averages of commuting flows over the four census years with available data (1981, 1991, 2001 and 2011), so they are not time-varying.

Standard errors are clustered on the ward level. We report specifications in which we estimate the model in first-differences as written in (21), but also in levels when we include area fixed effects and cumulate the Bartik shocks. We also report both OLS and IV estimates. The main challenge for OLS is the endogeneity of population to employment opportunities: see our model of migration below. In our IV specification, we instrument the population variables using the Altonji-Card instrument (which predicts foreign migration) described above, and applying the same Markov matrix (from (21)) to the Altonji-Card shift-shares as we apply to population variables themselves.

Panel B of Table 4 shows that the first stages are strong, with each endogenous variable most strongly affected by the Altonji-Card instrument that uses the same Markov matrix. Turning to Panel A, there is a robust positive correlation between the estimated value of $\log Z_{bt}$ and the current Bartik shock. The weighted average of neighboring Bartiks does not have the expected sign in the OLS regressions, but does have the expected positive sign in

---

goods however, the effect of population need not be negative: a larger population raises consumer demand, and hence labor demand and employment. The model can be expanded to account for this case, but the algebra becomes much more complicated for little gain in insight, and the empirical specification would be unaffected.

IV. Population has, on average, a positive association with $\log Z_{bt}$ in OLS, but this could be explained by the fact that people migrate to areas with higher wages. When we instrument population, we find an overall negative impact - though the two weighted averages have opposite signs and quite large magnitudes. This could be because the two weighted averages of population have a correlation coefficient of 0.93, so it is hard to distinguish between them empirically. Overall these estimates lend support to the model.

4.5 Determination of the employment rate

Deriving an estimating equation for the employment rate

In our analysis of commuting, we condition on individuals in work. The equation for the local employment rate (14) is not directly estimable, as we do not have data on housing costs for most of our sample period. But in Appendix D (specifically equation (A20)), we show how the model of the local economy outlined above can be used to express the change in the log employment rate, $\Delta \log \frac{N_{at}}{L_{at}}$, in terms of changes in the inclusive value from working IV_{at}^n and working-age population L_{at}:

$$
\begin{aligned}
\Delta \log \frac{N_{at}}{L_{at}} &= \frac{\psi \left(\epsilon^{hd} + \epsilon^{hs} - \phi \zeta \gamma_2 \right) \Delta IV_{at}^n - \psi \phi \zeta \Delta \log L_{at}}{\epsilon^{hd} + \epsilon^{hs} + \psi \phi \zeta \gamma_1} + TimeEffects \qquad (22) \\
&= \kappa_1 \Delta IV_{at}^n - \kappa_2 \Delta \log L_{at} + TimeEffects
\end{aligned}
$$

Notice the coefficient on the inclusive value is different in (14) and (22), a consequence of accounting for the endogeneity of local prices (and controlling for population). Conditional on the inclusive value, the effect of population on the local employment rate comes entirely through the impact on local housing prices.

The inclusive value from working, i.e. (13), can be estimated from the commuting model in the following way:

$$
\begin{aligned}
\Delta IV_{at}^n &= \Delta \log \sum_b \left(e^{d_{ab} + \phi \log W_{bt}} \right) = \Delta \log \sum_b \left[e^{d_{ab} + \phi \log W_{b1} + \phi (\log W_{bt} - \log W_{b1})} \right] \qquad (23) \\
&= \Delta \log \sum_b D_{ab} Z_{bt} + TimeEffects
\end{aligned}
$$

where the final line follows from (9) and (10). D_{ab} and Z_{bt} have been estimated in the commuting model, so these results can be used to obtain an estimate of ΔIV_{at}^n.

Estimates of employment rate response

We report OLS and IV estimates of (22) in Table 5, both including and excluding the population change. We report specifications both in first difference form, as in (22), and also in levels (where we control for area fixed effects). Standard errors are clustered by ward.

There are a number of issues in estimating this equation by OLS: e.g. the responsiveness of population to employment opportunities, and the fact that the inclusive value is a generated variable with considerable measurement error. We use two instruments for our two endogenous variables. The first is a weighted average of local Bartiks, $\sum_b \omega_{ab} \Delta \log X_{bt}$, where ω_{ab} is the fraction of employed area a residents who commute to area b (averaged over the full sample). And the second is the local Altonji-Card instrument described above. The estimates in Table 4 already show that Z_{bt} is correlated with the weighted Bartik instrument, so it is not surprising that the first stages (Panel B of Table 5) are strong, with both instruments significantly related to both endogenous variables (with intuitive signs). Turning to the second stage in Panel A, there is a robust positive correlation between the inclusive value and employment rate. The effect is stronger in IV than OLS, as one might expect given measurement error in the inclusive value. It is also stronger in the FE than FD specification. Local population generally has a negative effect on the employment rate, as predicted by the model. Overall, these estimates lend support to the model.

So far, we have developed a model of commuting, how commuting patterns respond to economic shocks and used this to model the employment rate. All of this has been conditional on the local population (though this has been instrumented where appropriate) which also affects the employment rate. The next section develops a simple model of migration to endogenize the local population.

5 Migration model

5.1 Estimating equation

So far, we have taken local population as given, but we now consider how population itself is determined. As in Amior and Manning (2018), we assume that population growth is increasing in local utility, but we allow this adjustment process to take time. More specifically,

20 20

denoting the expected utility from living in area a at time t is $\overline{U}_a(t)$:

$$
\begin{aligned}
\frac{\partial \log L_a(t)}{\partial t} &= m\overline{U}_a(t) + TimeEffects &\text{(24)}\\
&= m\left[V_{a0}(t) + \Psi\left(\frac{N_a(t)}{L_a(t)}\right)\right] + TimeEffects \\
&= \phi_{0a}(t) + \gamma_0 \log \frac{N_a(t)}{L_a(t)} + TimeEffects
\end{aligned}
$$

where the second equality exploits the sufficient statistic result (5): that the expected utility $\overline{U}_a(t)$ of living in an area can be summarized by the out-of-work utility V_{a0} and the employment rate. The third line then replaces out-of-work utility with a local amenity value $\phi_{0a}(t)$, using (6). As above, we have assumed that out-of-work utility is regionally invariant; and we have also linearized the effect of the employment rate. In the steady-state (where the local population distribution is stable), utility must be regionally invariant - satisfying the "spatial arbitrage" condition (Rosen, 1979; Roback, 1982). But sluggish adjustment of population (i.e. with $\gamma_0 < \infty$) means that utility can vary across areas, out of steady-state.

Equation (24) is written in continuous time. As Amior and Manning (2018) show, (24) can be discretized to yield the following estimating equation:

$$
\Delta \log L_{at} = \beta_0 + \beta_1 \Delta \log N_{at} + \beta_2 \log \frac{N_{at-1}}{L_{at-1}} + \beta_3 \Delta\phi_{0at} + \beta_4\phi_{0at-1} + TimeEffects + \varepsilon_{at} \quad \text{(25)}
$$

which has the form of an error correction mechanism (ECM). On the one hand, the change in log population $\Delta \log L_{at}$ responds to contemporaneous local employment shocks ΔN_{at}. But to the extent that adjustment is sluggish, local population will also respond to the initial deviation from steady-state, as represented by the initial employment rate $\log \frac{N_{at-1}}{L_{at-1}}$.

As Amior and Manning (2018) argue, the ECM model offers an intuitive way to assess the speed of population adjustment - as a "race" against employment growth. Like the modern labor-urban literature (e.g. Notowidigdo, 2011; Autor, Dorn and Hanson, 2013; Beaudry, Green and Sand, 2014), our approach accounts for the importance of contemporaneous shocks - essential for the long census intervals which we study. But it also integrates elements of the dynamic analysis of Blanchard and Katz (1992), thereby accounting for incomplete adjustment.

If population adjusts instantaneously to employment shocks, β_1 would take a value of 1. And controlling for employment changes, β_2 would equal 1 if local population adjustment over one decade is sufficient to compensate for initial deviations in the local employment

rate. Practically though, if $\beta_1 = 1$, it would not be possible to identify β_2 since there would be no observable deviations from the steady-state.

To control for the supply effects, $\Delta\phi_{0at}$ and ϕ_{0at-1}, we include the current and lagged Altonji-Card migrant shift-shares on the right hand side, as well as time-invariant climate effects.[19] In some specifications, we replace these time-invariant characteristics with area a fixed effects. Any unobservable amenity or supply shocks will fall into the ε_{at} error term. Given these unobservable effects may be correlated with local employment, we require instruments. Following Amior and Manning (2018), we instrument the current employment change $\Delta \log N_{at}$ with a current Bartik shock and the lagged employment rate $\log \frac{N_{at-1}}{L_{at-1}}$ using a lagged Bartik. Similarly to the employment rate response in Table 5, we use a weighted average of local Bartiks, $\sum_b \omega_{ab} \Delta \log X_{bt}$, where ω_{ab} is the fraction of employed area a residents who commute to area b (averaged over the full sample).

5.2 Results

We report the results in Table 6. Generally speaking, the estimates suggest that population responds strongly to local employment shocks, but not sufficiently to undo the effects of a shock within a decade. Column 1 of Panel A offers ward-level OLS estimates of (25), with β_1 and β_2 equal to 0.90 and 0.17 respectively. Omitted supply effects are likely to be a problem here, and we apply our Bartik instruments in column 2. The corresponding first stage estimates can be found in columns 1 and 4 of Panel B. We are able to separately identify the two endogenous variables: the current Bartik positively affects the contemporaneous employment change, and the lagged Bartik the lagged employment rate. As one might expect (and similarly to Amior and Manning, 2018), the IV estimate of β_1 (0.39) lies below the OLS estimate: a consequence presumably of omitted supply shocks. And the IV estimate of β_2 (0.52) exceeds the OLS estimate: intuitively, omitted supply shocks should raise population growth while reducing the employment rate. The standard errors of the IV estimates are small, below 0.1 for each coefficient.

Once we include ward fixed effects (column 3), the IV estimate of β_1 expands to 0.64 and β_2 drops to 0.47. The corresponding first stage estimates in columns 2 and 5 of Panel

---

[19]Rappaport (2007) shows that individuals have increasingly located in US cities with pleasant weather, and Cheshire and Magrini (2006) find similar trends for European regions. See noted under Table 6 for details of our climate controls.

B follow the same pattern as before. Interestingly, the population response is substantial even within TTWAs: this is demonstrated by the large coefficients in column 4, where we control for interacted TTWA-year fixed effects. β_1 is now substantially larger (reaching 0.88), perhaps indicating swifter adjustment over smaller distances. However, we cannot successfully identify β_2: it now takes a negative value, with its standard error ballooning to 0.5. This may reflect messier correlations in the first stage: see column 3 of Panel B in particular. Of course, the inclusion of these fixed effects is very demanding empirically.

Our coefficient estimates are similar to those we found in the US (Amior and Manning, 2018). But they are at very different spatial scales: wards for Britain and commuting zones for the US. For the sake of comparability, we now offer estimates of the population response across TTWAs, a closer match to commuting zones (see Table 1). This exercise also offers a useful specification test for our underlying model: in principle, the sufficient statistic result in Section 3 should be valid at any level of spatial aggregation, so we should expect similar population responses at ward and TTWA level.

We report our TTWA-level estimates in columns 5-7 of Panel A. The corresponding first stage estimates are reported in Panel C: we again see the correct instruments driving the correct endogenous variables. Our OLS and IV estimates are similar for TTWAs, with β_1 now (surprisingly) a little smaller for IV. But the key message is that our IV estimates are similar for wards and TTWAs, especially once we control for local fixed effects.

The similarity between the British and American adjustment process might be thought surprising. Much of the existing literature identifies larger population responses in the US than Britain or Continental Europe, mostly based on the VAR model of Blanchard and Katz (1992): see e.g. Decressin and Fatás (1995), Jimeno and Bentolila (1998), Obstfeld and Peri (1998), Beyer and Smets (2015) and Dao, Furceri and Loungani (2017). Bertola and Ichino (1995) and Decressin and Fatás (1995) suggest that institutional differences between the US and Europe (e.g. wage-setting practices, early retirement and disability schemes) may be responsible, while Rupert and Wasmer (2012) stress the role of housing market frictions.

For Britain in particular, there is a large existing literature on how internal migration responds to economic factors, including unemployment, vacancies, wages and the cost of living (mostly measured by house prices): see e.g. Hughes and McCormick (1981, 1987, 1994); Pissarides and Wadsworth (1989); Pissarides and McMaster (1990); Jackman and Savouri (1992); Gordon and Molho (1998); Henley (1998); Böheim and Taylor (2002); Gregg, Machin and Manning (2004); Hatton and Tani (2005); Andrews, Clark and Whittaker (2011); Rabe and Taylor (2012); and see McCormick (1997) for a brief survey of the findings to that

date. Most of the literature is now quite old, perhaps surprising considering improvements in data availability and the continued prominence of regional inequalities. The general theme is that regional migration in Britain does respond to economic factors, but sluggishly - such that adjustment to equilibrium is very slow.

Our evidence here suggests that population responses in Britain are perhaps larger than previously thought. At the same time, there is accumulating evidence that the US is not so exceptional. Local demand shocks in the US have long-lasting impacts on economic opportunity (Autor, Dorn and Hanson, 2013; Yagan, 2017), and spatial differences in joblessness are very persistent (Overman and Puga, 2002; OECD, 2005; Kline and Moretti, 2013). Amior and Manning (2018) argue this persistence is largely driven by serial correlation in the demand shocks themselves: though population does respond strongly, it cannot keep up with the change demand. And as we show in this paper, the story appears to be similar in Britain.

6   Effectiveness of commuting and migration in reducing spatial inequalities

In principle, both commuting and migration can help mitigate the impact of local demand shocks. This section assesses how effective they are in practice. The effectiveness depends partly of the responsiveness of commuting and migration to demand shocks, but also on the spatial and temporal correlation of those shocks. Commuting will not be an effective mechanism if shocks have a high level of spatial correlation, and migration will be less effective the higher the level of temporal correlation.

6.1   Spatial correlation in shocks

The possibility of commuting elsewhere offers insurance against local demand shocks. The value of this insurance depends on the spatial correlation of shocks: if demand shocks in neighboring areas are strongly correlated with local shocks, then its value is small. This section uses our theoretical framework to assess the spatial correlation in shocks. From (13), the change in the inclusive value from working in area a at date t can be approximated by:

$$\Delta IV_{at}^n \approx \sum_b \omega_{ab} \Delta \log Z_{bt} \tag{26}$$

where ω_{ab} is the fraction of employed area a residents who commute to area b (averaged over all years): see (11). To study the value of "commuting insurance" against local shocks, consider the expected value of ΔIV_{at}^n conditional on the local shock ΔZ_{at}:

$$
\begin{aligned}
E\left[\Delta IV_{at}^n | \Delta Z_{at}\right] & = \omega_{aa}\Delta \log Z_{at} + (1-\omega_{aa})\, E\left[\sum_{b \neq a} \tilde{\omega}_{ab}\Delta \log Z_{bt} | \Delta \log Z_{at}\right] \qquad (27) \\
& = \left[\omega_{aa} + (1-\omega_{aa})\, M_{at}\right]\Delta \log Z_{at}
\end{aligned}
$$

where $\tilde{\omega}_{ab} \equiv \frac{\omega_{ab}}{1-\omega_{aa}}$ is the commuting share excluding individuals who work locally. And M_{at} is the coefficient from a regression of $\sum_{b \neq a} \tilde{\omega}_{ab}\Delta \log Z_{bt}$ on $\Delta \log Z_{at}$. M_{at} is one way of expressing Moran's I (Moran, 1950), a common measure of spatial autocorrelation (see Anselin, 1995, for this formulation), in which the weights on the shocks in surrounding areas are the probability of commuting to those areas conditional on working outside the own-ward.

Notice how Moran's I emerges naturally from our model, as a measure of the commuting insurance against local shocks. The insurance value is large when the inclusive value from living in area a is insensitive to local demand shocks, i.e. when $[\omega_{aa} + (1-\omega_{aa})\, M_{at}]$ is small. This can either be because ω_{aa} is low (few residents work locally) or if M_{at} is low - in which case there is a low (or even negative) correlation between local demand shocks and demand shocks in neighboring areas.

We can get some idea of the extent of spatial correlation by computing $\sum_{b \neq a} \tilde{\omega}_{ab}\Delta \log Z_{bt}$ for every area and year, and then regressing it on $\Delta \log Z_{at}$. Table 7 shows what happens if this is done. In this regression, we use the average commuting flows over all census years to compute $\tilde{\omega}_{ab}$, together with our estimated values of $\Delta \log Z_{bt}$. Column 1 estimates a Moran's I of 0.146, after pooling all years and without ward fixed effects (this equation is effectively in first-differences, so it is not obvious they should be included). This is a modest positive spatial autocorrelation. Columns 2-4 estimate the degree of spatial correlation separately for each of the census years. Spatial correlation is much higher in the 1980s and zero for the 1990s. Column 5 includes ward fixed effects (for the full year sample), but this makes little difference.

One problem with the top row of Table 7 is that we only have imperfect estimates of the $\Delta \log Z_{at}$, so there is some measurement error. The estimate of Moran's I may then be biased downwards because of attenuation bias. One way of dealing with these problems is

to try to relate to the underlying Bartik and population shocks, using the model of (21). To this end, in the subsequent rows of the table, we report estimates of Moran's I for each of the four elements on the right-hand side of (21): i.e. the own-ward Bartik, a weighted average of Bartik shocks in the surrounding areas, and similarly for local population shocks.

The results can be summarized as follows. Both the Bartik and population shocks show a higher degree of spatial correlation than the estimated values of $\Delta \log Z_{at}$, and the weighted Bartik and population shocks give even larger numbers.[20] The spatial correlation of the shocks is now more similar across decades. One way of combining these different shocks is to compute a weighted average in line with (21), where we apply the FE IV estimates of the α parameters from Table 4. We report our estimates in the sixth row of Table 7: they are quite stable across specifications (hovering around 0.2), suggesting a modest positive level of spatial autocorrelation in shocks. It is also interesting to compare the degree of spatial correlation with that in the log employment rate itself: we report Moran's I for both the level and change in the final two rows of Table 4. The log employment rate (both level and changes) shows a somewhat higher degree of spatial correlation (about 0.4) than our composite shock, perhaps because we cannot observe all shocks. However, the difference in the estimates is not enormous.

The results presented so far estimate the average degree of spatial correlation, but there may also be interesting heterogeneity. We investigate whether the extent of spatial correlation varies with the share of manufacturing in 1981 and the level of the employment rate in 1981. The results are presented in Table 8 for $\Delta \log Z_{at}$ (the first three columns) and the composite shock (the last three columns). The interactions are normalized to zero at the sample means of the interacting variables, so the main effect can be interpreted as Moran's I for an area with average characteristics. Although the baseline Moran's I is similar for the two dependent variables, the interactions are rather different. For $\Delta \log Z_{at}$, there seems to be no relationship between the spatial correlation of shocks and the manufacturing share; but those areas with a high initial employment rate face significantly larger spatial correlation. For the composite shock, the ex-industrial and lower-employment areas are estimated to have significantly larger spatial autocorrelation in shocks. This suggests that commuting provides less insurance against local shocks in such places.

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[20]This is to be expected: the weighted shocks are regressed on a weighted set of weighted shocks, and the weights are Markov matrices. As the number of convolutions increases, the Markov matrix will converge, and the correlation will tend to 1.

6.2 Spatial distribution of the impact of demand shocks

One other question of interest is the spatial impact of demand shocks. (21) shows how shocks to labor demand are predicted to affect the returns to working in different areas. In turn, these returns affect the inclusive value of living in every area (through (26)), and this then affects the log employment rate for the residents of every area (as in (22)). Using (21), (22) and (26), the change in the log employment rate (in every area) can be reduced to the full set of Bartik and population shocks:

$$
\begin{aligned}
\Delta \log \frac{\mathbf{N_t}}{\mathbf{L_t}} &= \alpha_2 \kappa_1 \mathbf{\Omega^{nr}} \left[I + \alpha_1 \mathbf{\Omega^{nw}} \mathbf{\Omega^{nr}} \right] \Delta \log \mathbf{X_t} \\
&\quad - \left[\kappa_2 I + \alpha_3 \kappa_1 \mathbf{\Omega^{nr}} \left[I + \alpha_1 \mathbf{\Omega^{nw}} \mathbf{\Omega^{nr}} \right] \mathbf{\Omega^{nw}} \right] \Delta \log \mathbf{L_t} \\
&= \mathbf{\Omega^{nr}} \left[\mathbf{A_1} \Delta \log \mathbf{X_t} - \mathbf{A_2} \Delta \log \mathbf{L_t} \right]
\end{aligned}
\tag{28}
$$

Consider the impact of the Bartik shocks $\Delta \log \mathbf{X_t}$: this consists of two terms. The first is the matrix $\mathbf{\Omega^{nr}}$ which has individual elements ω_{ab}: i.e. the impact of an area b shock on area a residents depends on the fraction of these residents who commute to b. This matrix consists mostly of zeros, because most areas are not linked through direct commutes. The second term is a matrix $\mathbf{\Omega^{nr}} \mathbf{\Omega^{nw}} \mathbf{\Omega^{nr}}$: this measures the impact of shocks in one area on wages in other areas, which comes through the interaction between labor markets in different areas. This matrix has almost no zeroes (although many elements are very small), implying that a shock in almost every area affects the employment rate in almost every other area, even if only to a small extent.

Using (28), we now attempt to summarize the spatial distribution of the shocks' impact. Our approach is to consider a Bartik shock for each area, work out the total impact on every other area, and then compute the share of the total impact on every area that is the result of shocks occurring within a certain distance of the area. We do this exercise for a shock in every area and then take the mean of the spatial distribution of the shocks. This can be interpreted as a "spatial impulse response". The results are shown in Figure 5, where we use the IV estimates with fixed effects from Panel A, column 3 of Table 4, as well as the estimates from Panel A, column 5 of Table 5. This exercise has some similarities to that considered by Monte, Redding and Rossi-Hansberg (2018), who argue that the impact of a local demand shock on local employment varies across areas according to the strength of commuting ties: this will also be the case in our framework. However, they do not consider the impact of local demand shocks on areas other than the one experiencing the shock - and we deviate in this respect. It is also worth emphasizing again that they study an economy

in steady-state, whereas our entire focus is on spatial disparities in welfare (as summarized by the local employment rate).

For the Bartik shock $\Delta \log \mathbf{X_t}$, 50 percent of the total impact occurs within 9km of the shock and 90 percent within 50km. The impact of shocks is very local because commutes are generally short, though the impact of the Bartik shocks is not as local as commuting itself. For comparison, 50 percent of commutes are shorter than 5km and 90 percent shorter than 30km. The reason that the impact of demand shocks are somewhat less local than commuting is because of the mechanisms that link wages in different areas: these cause the impact of shocks to ripple out to other areas (as in Manning and Petrongolo, 2017).

6.3   Combining the commuting and migration models

In this section, we combine the commuting, local economy and migration models to assess the role that demand shocks play in accounting for persistence in joblessness across local areas. The commuting and local economy models lead to an equation in which the employment rate in every area can be written as a function of the demand shocks and the change in population, as represented in (28). Now express local population adjustment $\Delta \log \mathbf{L_t}$ in terms of local employment rates, using the migration model (25). After some rearrangement, this can be written as:

$$\Delta \log \frac{\mathbf{N_t}}{\mathbf{L_t}} = \mathbf{A_1} \Delta \log \mathbf{X_t} - \mathbf{A_2} \left[\frac{\beta_1}{1 - \beta_1} \Delta \log \frac{\mathbf{N_t}}{\mathbf{L_t}} + \frac{\beta_2}{1 - \beta_1} \log \frac{\mathbf{N_{t-1}}}{\mathbf{L_{t-1}}} \right] + TimeEffects \quad (29)$$

which be expressed as an ECM for the log employment rate, in terms of the demand shocks alone:

$$\Delta \log \frac{\mathbf{N_t}}{\mathbf{L_t}} = \left[\mathbf{I} + \frac{\beta_1}{1 - \beta_1} \mathbf{A_2} \right]^{-1} \mathbf{A_1} \Delta \log \mathbf{X_t} - \frac{\beta_2}{1 - \beta_1} \left[\mathbf{I} + \frac{\beta_1}{1 - \beta_1} \mathbf{A_2} \right]^{-1} \mathbf{A_2} \log \frac{\mathbf{N_{t-1}}}{\mathbf{L_{t-1}}} + TimeEffects$$
$$(30)$$

(30) gives a dynamic equation for how both spatial and temporal differences in employment rates can be explained by the pattern of shocks. It should be noted that this is not suitable for assessing how demand shocks affect the overall employment rate, as that will partly be included in the time effects. What it can do is explain variation in employment rates across areas. The pattern of linkages in (30) is complicated and hard to summarize. One way to do

this is to assume that local demand shocks are constant over time (i.e. the level of demand follows a trend), though different across areas: denote this by $\Delta \log \mathbf{X}$. A well-known feature of ECMs is that these persistent shocks will generate permanent differences in employment rates across areas, as there will only be population movements across areas if there are differences in employment rates. Using (30), the resulting disparities in local employment rates are given by:

$$\log \frac{\mathbf{N}}{\mathbf{L}} = \frac{1 - \beta_1}{\beta_2} \mathbf{A_2^{-1}} \mathbf{A_1} \Delta \log \mathbf{X} \tag{31}$$

Note that these disparities will be influenced by the spatial interactions and the speed of the population adjustment process.[21] For a given pattern of demand shocks and spatial interactions, a swifter migratory response (i.e. larger β_1 or β_2 in (25)) will narrow the local employment rate differentials. But the patterns of commuting, as represented by the matrices $\mathbf{A_1}$ and $\mathbf{A_2}$, will also affect the transmission of local demand shocks (across areas) into the spatial distribution of employment rates. One way to quantify this is to consider how reductions in commuting costs affect local adjustment.

6.4 Impact of commuting costs on the spatial distribution of employment rates

We now consider the impact of a change in commuting costs, driven perhaps by infrastructure investment. It is natural to model this as a change in the cost of distance, d_{ab}, in (6). We model this as an implicit reduction of all distances by a fraction δ. Specifically, in the equation for d_{ab} in (12), a log distance of $\log dist$ is replaced by $\log dist (1 - \delta)$. We then predict the effect on commuting patterns using (8), and we study the implications for the matrices $(\mathbf{\Omega^{nr}}, \mathbf{\Omega^{nw}})$ and also $(\mathbf{A_1}, \mathbf{A_2})$ in (28).

What are the consequences for the spatial distribution of employment rates? To answer this question, we require an estimate of $\Delta \log \mathbf{X}$ to insert into (31). To this end, we take the average of the employment rates and commuting flows across areas over our full sample; and using (31), we then back out the implied pattern of demand shocks.[22] We then consider what happens when we change the commuting costs and commuting matrices. Our model delivers a prediction for how the employment rate will change in every area up to a common effect.

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[21](31) should be interpreted as an approximation because, over long periods, there will also be adjustments in commuting patterns that would cause the matrices $\mathbf{A_1}$ and $\mathbf{A_2}$ to change. But the observed change in commuting patterns in our data imply only small changes, so we omit this consideration for ease of exposition.

[22]This should be regraded as a thought experiment designed to have plausible numbers. It is *not* a claim that all local differences in employment rates can be explained by demand shocks alone

This means that we cannot use this exercise to simulate the *absolute* changes in employment rates, but we can use it to simulate *relative* changes.

In Figure 6, we predict how the differential between the log 90th and 10th percentiles in local employment rates changes with commuting costs. With no change in commuting costs (i.e. $\delta = 0$), the log 90-10 is 0.22: this simply reflects the actual data. A decline in costs reduces local disparities, but the effect is not very large. For example, a 10 percent reduction (i.e. $\delta = 0.1$) causes the log 90-10 to fall by 0.009 (i.e. a 4 percent decrease); and the effect seems quite linear.

In comparison, an equivalent expansion of the migratory response causes a much larger reduction in local disparities. Specifically, increasing (β_1, β_2) by 10 percent causes the log 90-10 to fall from 0.222 to 0.167, a 24 percent reduction. One would need a 60 percent reduction in commuting costs to achieve a similar impact. Of course, in practice, a 10 percent increase in mobility rates might be harder to achieve than an equivalent reduction in commuting costs. In any case, the relativeness ineffectiveness of commuting in eliminating disparities is intuitive: most commutes are short, and local demand shocks have a high degree of spatial correlation. A large reduction in commuting costs is required to overcome this.

7 Conclusion

This paper assesses the respective roles of commuting and migration in equalizing economic opportunity. Our focus is the persistent inequalities in jobless rates across British neighborhoods, but we make a number of methodological contributions which have broader applications:

1. A generalization of Amior and Manning's (2018) result that the employment rate in an area can serve as an (easily computed) sufficient statistic for local economic opportunity - to the case where workers can work outside their area of residence.

2. A model of the commuting decision (i.e. the choice of area of work, conditional on area residence), which can be applied where there are a very large number of alternatives.

3. A model of the determination of the employment rate, among residents of some area, as a function of economic conditions in surrounding areas that are inferred from commuting patterns.

4. A model of migration between areas, which depends on local differentials in employment rates.

One feature of our framework is that it can be applied to any spatial scale and can readily accommodate a large number of areas. In our particular application, our model fits the data well. We find that both commuting and migration respond to local economic shocks, but that these responses are insufficient to equalize opportunity across areas in the face of demand shocks which are correlated across space and persistent over time. The spatial correlation in shocks limits the effectiveness of commuting as a means of equalizing employment rates, and the temporal correlation limits the effectiveness of migration. Facilitating commuting or migration would reduce spatial inequalities, though increasing migration would be more effective than increasing commuting. Still, the cost of substantially reducing these spatial frictions is likely to be prohibitive, and some other intervention may be required if these regional inequalities are to be addressed.

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Appendices

A   Further details on data

A.1   Population and employment counts

We rely on published small area counts of population and employment for individuals aged 16-64[23] from the decennial UK census, excluding Northern Ireland. We take our English and Welsh 2011 data from Nomis (*https://www.nomisweb.co.uk/census/2011*) and our Scottish 2011 data from National Records for Scotland (*http://www.scotlandscensus.gov.uk*). Scottish 2001 data was provided on DVD by the General Register Office for Scotland (*http://www.scrol.gov.uk*). We download all other UK census data from UK Data Service Census Support (*http://casweb.mimas.ac.uk*). All the small area counts are based on 100 percent samples, though some noise has been artificially injected into some small cells to preserve anonymity.

Using this data, we construct a panel of 9,975 Standard Table wards based on 2001 census definitions.[24] And in turn, we aggregate these to Travel-To-Work-Areas (TTWAs). More precisely, we use an approximation to the 2001 census' TTWA scheme which is perfectly identified by our Standard Table wards: specifically, we allocate each ward to the TTWA (2001 definition) which accounts for the largest share of its population.

The key challenge in constructing our data is changes in the definitions of geographical units across census years. To ensure maximum consistency with the 2001 Standard Table wards, we use the finest geographical data available in all other census years. These are known as enumeration districts in 1971, 1981 and 1991 and output areas in 2011, and they number between 120,000 and 230,000 depending on census year. Since they do not precisely identify the 2001 wards, we allocate population and employment proportionately by geographical area based on shapefiles downloaded from the UK Census Edina service (*https://census.edina.ac.uk*).

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[23]For the sake of consistency across census years, we code all full-time students as non-employed (in line with the pre-2001 convention). The data for 1971 includes population for 16-64s, but only includes the participation rate for 15-64s and the unemployment rate for individuals aged 16+. In that year, we impute the employment count by taking the product of the 16-64 population, the 15-64 participation rate and one minus the 16+ unemployment rate. All other census years allow us to construct employment counts precisely for 16-64s.

[24]There are in fact 9,976 Standard Table wards, but we aggregate Walney North and Walney South into a single ward because of problems with the 1971 geographical match.

37

A.2 Commuting flows

For our commuting analysis, we rely on the UK Census' Special Workplace Statistics (accessible at *http://cider.census.ac.uk*), which record commuting flows between every pair of local areas. Conveniently, this data is available for 2001 Standard Table wards for the 1981 and 1991 censuses. The 2001 data is available for geographical units which precisely identify Standard Table wards. And the 2011 data is available for 230,000 output areas which do not precisely identify these wards. Our strategy for 20111 is to allocate each output area to the Standard Table ward which accounts for the largest share of its geographical area (using shapefiles from *https://census.edina.ac.uk*), and we aggregate the commuting flows to ward-level on this basis. Unfortunately, there is no data available for 1971.

The flow data is broken down by various demographic categories (depending on census year), but we cannot observe flows of 16-64s for each year. Instead, we take the following approach. For each ward a, we compute the fraction of employed individuals working in each ward b. And we then impute the total flow from a to b by taking the product of these shares and the 16-64 employment count in ward a.

A.3 Industry data

To construct the Bartik shift-share in (1), we require a disaggregation of local employment by industry. Nomis (*https://www.nomisweb.co.uk*) provides annual local counts of paid employees, by industry and workplace geography, sourced from administrative data going back to 1971. Our 1971 and 1981 data is based on the Census of Employment, our 1991 data on the Annual Employment Survey, our 2001 data on the Annual Business Inquiry, and 2011 on the Business Register Employment Survey.[25]

As always, the challenge is ensuring consistency in industry and geography definitions. Our 1971 and 1981 data is available for 3-digit Standard Industrial Classification (SIC) industries, our 1991 and 2001 data for 4-digit SIC 1992 industries, and our 2011 data for 5-digit SIC 2007 industries. We construct industry look-up tables with proportional allocations to convert all data to a 3-digit SIC 1992 classification with 212 industries, with a single category for agricultural employment. We estimate these allocations using longitudinal micro-data from the Annual Survey of Hours and Earnings (formerly the New Earnings Survey): this is administrative data based on a 1% sample of employees. Specifically, in those years where

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[25]*http://www.ons.gov.uk/ons/guide-method/method-quality/specific/labour-market/business-register-and-employment-survey–bres-/history-and-background/index.html*

there was a change of classification, we estimate transitions between industry codes - for those workers who remained in the same job.

Data on agricultural employment is incomplete in 1991, 2001 and 2011. We replace our ward-level agricultural counts in 1991 with data from the UK Census' Special Workplace Statistics (*http://cider.census.ac.uk*). Equivalent data is not available in 2001 and 2011, so we impute ward-level agricultural counts in those years by assuming agricultural employment grew at the same rate in all wards - and relying on national-level data on agricultural employment from the census.

In terms of geography, our 2011 data are available for 2001-definition Census Area Statistics wards, which perfectly identify our 2001 Standard Table wards in England and Wales. Nomis also provides the 2011 data for 6,505 Scottish Data Zones (equivalent to Lower Layer Super Output Areas), and we map these employment stocks onto the 1,176 Scottish Standard Table wards proportionally using allocations based on address counts.[26] Our 2001 and 1991 data area are based on 1991-definition wards. These number 10,764 in Britain; and as with Data Zones, we allocate these employment stocks to our 9,975 Standard Table Wards proportionally using address count shares.

Unfortunately, our data for 1971 and 1981 are much more coarse: these are only disaggregated into 309 1981-definition TTWAs. We disaggregate this data into wards by exploiting ward-level data from the 1991 cross-section. This procedure consists of three steps. First, we proportionally allocate 1991 employment in each ward to TTWAs, based on address count shares. Second, for each industry and TTWA, we compute the share of 1991 employment which lies in each ward. And finally, we used these 1991-based shares to disaggregate 1971 and 1981 TTWA employment into wards - by industry.

Finally, equivalent local workplace data prior to 1971 have not been digitized, but we do require a shift-share for 1961-71 (i.e. the lagged shift-share for the 1971-81 observation) to estimate the population response equation (25). We impute 1961 local industrial composition using (i) the 1971 local industry employment counts and (ii) national-level employment growth by industry over 1961-71 (compiled by Department of Employment, 1975); and assuming that industry i employment in every geographical area grew at the national industry i rate over 1961-71.

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[26]These allocations are based on the National Postcode Directory, provided by the UK Data Service Census Support: *http://edina.ac.uk/census/*.

A.4 Migrant origins

To construct the Altonji-Card instrument in equation (2), we require a local panel of migrant counts by country of origin. For each pair of census years, we use the greatest possible origin country detail. For the shift-share between 1971 and 1981, we use 10 origin country categories (apart from British-born): Ireland, Old Commonwealth (i.e. Canada, Australia and New Zealand), African Commonwealth, Caribbean Commonwealth, Far Eastern Commonwealth, India, Pakistan/Bangladesh, other Commonwealth, other Europe, and a residual category. For the period 1981-1991, we are able to use 12 categories: all of the above, except we are able to disaggregate Pakistan and Bangladesh into two categories, and we can split the African Commonwealth category into East African Commonwealth and other African Commonwealth. For the 1990s, we are restricted to 10 categories: these include all those for the 1980s, minus Caribbean Commonwealth and "other Commonwealth" (both of which we place into the residual category). For the 2000s, we are able to use 23 categories: Ireland, other EU members in 2001, Poland, other Europe, North Africa, Nigeria, other Central/Western Africa, Kenya, South Africa, Zimbabwe, other South/Eastern Africa, Middle East, Far East, Bangladesh, India, Pakistan, other South Asia, USA, other North America, South America, Caribbean, Oceania, and a residual category.

The published small-area census statistics of 1961 have not yet been digitized, but we require 1961 data to construct a shift-share for 1961-71 (i.e. the lagged shift-share for the 1971-81 observation) to estimate the population response equation (25). To this end, we rely on a 1961 microdata sample with broader geographical units (specifically 118 approximate TTWA groups): this data is described in the following section. We disaggregate our 1961 origin count data into wards by exploiting ward-level data from the 1971 cross-section. We apply the same three-step procedure as above (when we impute 1961 local industrial composition). First, we proportionally allocate 1971 origin counts in each ward to our 118 approximate TTWA groups, based on address count shares. Second, for each origin country and approximate TTWA group, we compute the share of 1971 employment which lies in each ward. And finally, we used these 1971-based shares to disaggregate our local 1961 origin counts into wards. We construct our 1961-71 shift-share using 9 (non-British) origin country categories: Ireland, Old Commonwealth, African Commonwealth, Caribbean Commonwealth, Far Eastern Commonwealth, India, Pakistan/Bangladesh, Sri Lanka, and a residual category.

A.5 Census microdata

The bulk of our analysis is conducted using published small-area aggregates from the UK census from 1971. But the census does provide microdata samples[27] from 1961, and we exploit these for two exercises: first, to estimate the persistence of composition-adjusted employment rates in Table 2; and second, to compute Altonji-Card migrant shift-shares for the period 1961-71. We use the microdata in the latter case, because the small-area aggregates of 1961 have not yet been digitized.

We use the 5 percent individual sample for 1961, 1971 and 1981; the 2 percent individual sample for 1991; the 5 percent Small Area Microdata sample for 2001; and the 5 percent Local Authority sample for 2011. Unfortunately, these microdata only identify relatively coarse geographical units (grouped local authorities), of which there are 254 in 1961, 238 in 1971, 278 in 1981 and 1991, 423 in 2001, and 285 in 2011. We then combine these into a set of 118 geographical areas: these approximate groups of TTWAs, and they can be perfectly identified using the microdata of each census year. Unfortunately, large parts of Huntingdon, Peterborough, Kent and Lancashire are omitted from the 1971 data[28]: this affects 15 geographical areas (out of our set of 118) in 1971, and we drop these observations for this year only.

A.6 Incremental spatial autocorrelation

In Figure 4 in the main text, we present "incremental" spatial autocorrelation estimates - to illustrate the extent of spatial correlation in local changes in employment rates. In this appendix, we explain how this is implemented. For every ward a and census year t, we compute the employment and population across all wards up to distance d away (excluding ward a), specifically:

$$N_{-a}^d = \sum_{b \neq a | dist_{ab} < d} N_b \tag{A1}$$

$$L_{-a}^d = \sum_{b \neq a | dist_{ab} < d} L_b \tag{A2}$$

where $dist_{ab}$ is the distance between wards a and b, and N_b and L_b are employment and population respectively in ward b. Distances are measured between wards' population-weighted centroids. For every distance d (1km, 2km, ... up to 30km), we then construct $\frac{N_{-a}^d}{L_{-a}^d}$, the em-

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[27]See *https://census.ukdataservice.ac.uk/get-data/microdata.aspx*

[28]See *http://doc.ukdataservice.ac.uk/doc/8268/mrdoc/pdf/8268_eehcm_cm_user_guide_v3.pdf.*

ployment rate across wards up to distance d away (excluding a). And for every distance d, we regress $\log \frac{N^d_{-a}}{L^d_{-a}}$ on $\log \frac{N_a}{L_a}$, the local employment rate in area a, controlling for a full set of census year effects. We report the coefficients in Figure 4, together with confidence intervals (with standard errors clustered by ward). Note that these estimates can be interpreted as Moran's I with weights of 1 applied to areas within distance d and 0 to all others: see the discussion in Section 6.

B   Proof of sufficient statistic result

B.1   Expected utility

Denote by G_b the derivative of G with respect to its bth argument. And let $\tilde{\omega}_{ab} = \frac{N_{ab}}{L_a}$ denote the probability of a resident of a choosing option b, where N_{ab} is the commuting flow from a to b, and L_a is local population. McFadden (1978) shows that $\tilde{\omega}_{ab}$ can be written as:

$$\tilde{\omega}_{ab} = \frac{e^{V_{ab}} G_b\left(e^{V_{a0}}, e^{V_{a1}}, .., e^{V_{aA}}\right)}{G\left(e^{V_{a0}}, e^{V_{a1}}, .., e^{V_{aA}}\right)} = \frac{e^{V_{ab}-V_{a0}} G_b\left(1, e^{V_{a1}-V_{a0}}, .., e^{V_{aA}-V_{a0}}\right)}{G\left(1, e^{V_{a1}-V_{a0}}, .., e^{V_{aA}-V_{a0}}\right)} \tag{A3}$$

where the second equality follows from the assumption that G is Hod1.

B.2   Limited IIA assumption

We now impose our assumption that the relative probability of any two employment options b and b', i.e. $\frac{\tilde{\omega}_{ab}}{\tilde{\omega}_{ab'}}$, is independent of V_0. Following McFadden (1978), this requires weak separability in G of the form:

$$G\left(e^{V_{a0}}, e^{V_{a1}}, .., e^{V_{aA}}\right) = G\left(e^{V_{a0}}, g\left(e^{V_{a1}}, .., e^{V_{aA}}\right)\right) \tag{A4}$$

where g is Hod1. To see that this restriction satisfies the Limited IIA assumption, notice that:

$$\tilde{\omega}_{ab} = \frac{e^{V_{ab}} G_g\left(e^{V_{a0}}, g\left(e^{V_{a1}}, .., e^{V_{aA}}\right)\right) g_b\left(e^{V_{a1}}, .., e^{V_{aA}}\right)}{G\left(e^{V_{a0}}, e^{V_{a1}}, .., e^{V_{aA}}\right)} \tag{A5}$$

so the relative employment probabilities van be written as:

$$\frac{\tilde{\omega}_{ab}}{\tilde{\omega}_{ab'}} = \frac{e^{V_{ab}} g_b\left(e^{V_{a1}}, .., e^{V_{aA}}\right)}{e^{V_{ab'}} g_{b'}\left(e^{V_{a1}}, .., e^{V_{aA}}\right)} \tag{A6}$$

which does not depend on V_{a0}.

B.3   The employment rate

Applying the limited IIA assumption to (A3), the local employment rate $\frac{N_a}{L_a} = 1 - \tilde{\omega}_{a0}$ can be written as:

$$1 - \frac{N_a}{L_a} = \frac{e^{V_{a0}} G_0 \left(e^{V_{a0}}, g \left(e^{V_{a1}}, .., e^{V_{aA}} \right) \right)}{G \left(e^{V_{a0}}, g \left(e^{V_{a1}}, .., e^{V_{aA}} \right) \right)} = \frac{G_0 \left(1, g \left(e^{V_{a1} - V_{a0}}, .., e^{V_{aA} - V_{a0}} \right) \right)}{G \left(1, g \left(e^{V_{a1} - V_{a0}}, .., e^{V_{aA} - V_{a0}} \right) \right)} \tag{A7}$$

where the second equality follows from the assumption that both G and g are Hod1. (A7) is a mapping from the value of g to the employment rate, i.e. all combinations of outside alternatives that offer the same value of g will yield the same employment rate. Given our assumption that the employment rate is elastic, $\frac{N_a}{L_a}$ must vary with g. And furthermore, this mapping must be monotonic. To see this, notice that (A7) can be written as:

$$1 - \frac{N_a}{L_a} = \frac{G(1, g) - g G_g(1, g)}{G(1, g)} = 1 - \frac{g G_g(1, g)}{G(1, g)} \tag{A8}$$

using Euler's theorem and the Hod1 property of G. The right hand side of (A8) is the elasticity of G with respect to g, which is necessarily monotonic. Given this, (A8) can be inverted (in the spirit of Hotz and Miller, 1993) to express g as an (increasing) function of the local employment rate, $\frac{N_a}{L_a}$. Denote this function as $g \left(\frac{N_a}{L_a} \right)$.

B.4   Expected utility

McFadden (1978) shows that the expected utility of a resident of a is given by:

$$\overline{U}_a = E \left(\max_b U_{ab} \right) = \log G \left(e^{V_{a0}}, e^{V_{a1}}, .., e^{V_{aA}} \right) + \gamma = V_{a0} + \log G \left(1, e^{V_{a1} - V_{a0}}, .., e^{V_{aA} - V_{a0}} \right) + \gamma \tag{A9}$$

where γ is Euler's constant, and the second equality follows from the fact that G is Hod1. This is often called the inclusive value. Given the IIA assumption, and given that g can be written in terms of the local employment rate, (A9) can be expressed as:

$$\overline{U}_a = V_{a0} + \log G \left(1, g \left(\frac{N_a}{L_a} \right) \right) + \gamma \tag{A10}$$

which has the form of (5).

C   Details of estimation procedure for commuting model

Denoting the number of commuters from a to b at time t as N_{abt} (which is the data available to us), the log-likelihood can be written (up to a constant that does not depend on parameters) as:

$$\log \mathcal{L} = \sum_{a,b,t} N_{abt} \log \omega_{abt} \tag{A11}$$

which can be maximized over (D_{ab}, Z_{bt}) subject to the constraints that: (i) D_{ab} sums to one for all a; (ii) Z_{bt} sums to one for all t; and (iii) $Z_{b1} = 1/A$. Using (11), (A11) can be written as:

$$\log \mathcal{L} = \sum_{a,b} \left(\sum_t N_{abt} \right) \log D_{ab} + \sum_{b,t} \left(\sum_a N_{abt} \right) \log Z_{bt} - \sum_{a,t} \left(\sum_b N_{abt} \right) \log \left(\sum_i D_{ai} Z_{it} \right) \tag{A12}$$

Define a multiplier μ_a^d for the constraint $\sum_b D_{ab} = 1$. Then, the first-order condition for the maximization of (A12) with respect to D_{ab} can be written as:

$$\frac{1}{D_{ab}} \sum_t N_{abt} - \sum_{i,t} \frac{Z_{bt}}{\sum_j D_{aj} Z_{jt}} N_{ait} - \mu_a^d = 0 \tag{A13}$$

Multiplying every term by D_{ab}, re-arranging and summing over b leads to:

$$\mu_a^d \sum_b D_{ab} = \sum_{b,t} N_{abt} - \sum_{i,b,t} \frac{D_{ab} Z_{bt}}{\sum_j D_{aj} Z_{jt}} N_{ait} = \sum_{b,t} N_{abt} - \sum_{i,t} \frac{\sum_b D_{ab} Z_{bt}}{\sum_j D_{aj} Z_{jt}} N_{ait} = \sum_{b,t} N_{abt} - \sum_{i,t} N_{ait} = 0 \tag{A14}$$

which implies that $\mu_a^d = 0$. Using this in (A13) and re-arranging leads to the following expression for the ML estimate of D_{ab}:

$$D_{ab} = \frac{\sum_t N_{abt}}{\sum_{i,t} \frac{Z_{bt}}{\sum_j D_{aj} Z_{jt}} N_{ait}} \tag{A15}$$

Now define a multiplier μ_t^z for the constraint $\sum_b Z_{bt} = 1$. Then, the first-order condition for the maximization of (A12) with respect to Z_{bt} can be written as:

$$\frac{1}{Z_{bt}} \sum_a N_{abt} - \sum_{a,i} \frac{D_{ab}}{\sum_j D_{aj} Z_{jt}} N_{ait} - \mu_t^z = 0 \tag{A16}$$

Multiplying every term by Z_{bt}, re-arranging and summing over b leads to:

$$\mu_t^z \sum_b Z_{bt} = \sum_{a,b} N_{abt} - \sum_{a,i,b} \frac{D_{ab} Z_{bt}}{\sum_j D_{aj} Z_{jt}} N_{ait} = \sum_{a,b} N_{abt} - \sum_{a,i} \frac{\sum_b D_{ab} Z_{bt}}{\sum_j D_{aj} Z_{jt}} N_{ait} = \sum_{a,b} N_{abt} - \sum_{a,i} N_{ait} = 0 \tag{A17}$$

which implies that $\mu_a^z = 0$. Using this in (A16) and re-arranging leads to the following expression for the ML estimate of D_{ab}:

$$Z_{bt} = \frac{\sum_a N_{abt}}{\sum_{a,i} \frac{D_{ab}}{\sum_j D_{aj} Z_{jt}} N_{ait}} \tag{A18}$$

If there are A areas and T time periods, the likelihood function (A12) contains $A(A-1)$ parameters in D_{ab} and $(A-1)(T-1)$ parameters in Z_{bt} (all after allowing for the normalizations), approximately 99.5m parameters, so that estimation is not straightforward in practice. We simplify the problem using an EM-algorithm: given an initial set of parameters, one can update the parameters using the closed-form expressions in (A15) and (A18), and this process converges to the ML estimates.

D   Wage determination

In this section, we derive a log-linear approximation for how local wages respond to labor demand and population shocks in different areas. The aim is to derive an estimating equation which conditions on time effects. For this reason, we do not derive expressions for changes in aggregate quantities that affect all areas equally. In the interests of economy of notation, we suppress the time effects in the derivation, but they are present in all equations.

Using (19) and 20, we obtain the following equation for the change in log housing prices:

$$\Delta \log Q_{at}^h = \frac{1}{\epsilon^{hd} + \epsilon^{hs}} \left(\Delta \log L_{at} + \gamma_1 \Delta \log \frac{N_{at}}{L_{at}} + \gamma_2 \Delta IV_{at}^n \right) \tag{A19}$$

Substituting (A19) into (14) and re-arranging leads to:

$$\Delta \log \frac{N_{at}}{L_{at}} = \frac{\psi \left(\epsilon^{hd} + \epsilon^{hs} - \phi \zeta \gamma_2 \right) \Delta IV_{at}^n - \psi \phi \zeta \Delta \log L_{at}}{\epsilon^{hd} + \epsilon^{hs} + \psi \phi \zeta \gamma_1} \tag{A20}$$

which, abstracting from time effects, is equation (22) in the main text. And substituting

(A20) back into (A19) gives:

$$\Delta \log Q_{at}^h = \frac{\Delta \log L_{at} + (\gamma_1 \psi + \gamma_2) \Delta IV_{at}^n}{\epsilon^{hd} + \epsilon^{hs} + \psi\phi\zeta\gamma_1} \tag{A21}$$

Now, using (8) and (13), the inclusive value of working for residents of area a can be approximated in log-linear form as:

$$\Delta IV_{at}^n \approx \phi \sum_b \omega_{ab} \Delta \log W_{bt} \tag{A22}$$

That is, the change in the inclusive value of working is a weighted average of the change in log wages, where the weights are the probability of working in different areas. To make further progress, it is convenient to express this in matrix form. We denote the vector of a variable by putting it in bold and dropping the area subscript. So, (A22) can be written as:

$$\Delta \mathbf{IV_t^n} = \phi \mathbf{\Omega^{nr}} \Delta \log \mathbf{W_t} \tag{A23}$$

where $\mathbf{\Omega^{nr}}$ is a non-negative weighting matrix whose rows all sum to one. The bth column of the ath row represents the share of employed area a residents who work in area b, i.e. the elements are ω_{ab}. Using (A23) and (A20), the change in the vector of employment of residents (across areas) is:

$$\Delta \log \mathbf{N_t} = \frac{\phi\psi \left(\epsilon^{hd} + \epsilon^{hs} - \phi\zeta\gamma_2\right) \mathbf{\Omega^{nr}} \Delta \log \mathbf{W_t} + \left[\epsilon^{hd} + \epsilon^{hs} - \psi\phi\zeta (1 - \gamma_1)\right] \Delta \log \mathbf{L_t}}{\epsilon^{hd} + \epsilon^{hs} + \psi\phi\zeta\gamma_1} \tag{A24}$$

Now, using (15) and (16), the change in the vector of labor supplies to different areas is:

$$\Delta \log \mathbf{N_t^w} = \phi \mathbf{\Delta \log W_t} - \mathbf{\Omega^{nw}} \left[(1 - \psi) \Delta \mathbf{IV_t^n} + \psi\phi\zeta\Delta \log \mathbf{Q_t^h}\right] + \mathbf{\Omega^{nw}} \Delta \log \mathbf{L_t} \tag{A25}$$

where $\mathbf{\Omega^{nw}}$ is a non-negative weighting matrix whose rows sum to one. The jth column of the ith row represents the share of area i employees who reside in area j. Substituting (A21) and (A23) for $\Delta \mathbf{IV_t^n}$ and $\Delta \log \mathbf{Q_t^h}$ respectively in (A25) then gives:

$$\begin{aligned}
\Delta \log \mathbf{N_t^w} &= \phi \left[\mathbf{I} - \left(1 - \psi + \frac{\psi\phi\zeta (\gamma_1\psi + \gamma_2)}{\epsilon^{hd} + \epsilon^{hs} + \psi\phi\zeta\gamma_1}\right) \mathbf{\Omega^{nw}}\mathbf{\Omega^{nr}}\right] \mathbf{\Delta \log W_t} \\
&+ \left(1 - \frac{\psi\phi\zeta}{\epsilon^{hd} + \epsilon^{hs} + \psi\phi\zeta\gamma_1}\right) \mathbf{\Omega^{nw}} \Delta \log \mathbf{L_t}
\end{aligned} \tag{A26}$$

which expresses labor supply to every area as a function of wages and population.

Now consider the labor demand side. Combining (17) and (18) to eliminate prices, we have:

$$\Delta \log \mathbf{N_t^w} = \frac{\Delta \log \mathbf{X_t} + (\theta - 1) \Delta \log \mathbf{A_t} - \theta \Delta \log \mathbf{W_t}}{1 + \varphi - \theta \varphi} \tag{A27}$$

where one needs to assume the denominator is positive for the model to be well-behaved. It is clear from (A27) that one cannot distinguish between taste shocks $\Delta \log \mathbf{X_t}$ and technology shocks $\Delta \log \mathbf{A_t}$ using data on employment and wages alone. To keep notation simple, we only include the taste shocks $\Delta \log \mathbf{X_t}$ from now on. Combining (A26) and (A27) leads to the following expression for the change in wages as a function of demand shocks and (supply-driven) population changes:

$$\Delta \log \mathbf{W_t} = \alpha_1 \mathbf{\Omega^{nw} \Omega^{nr}} \Delta \log \mathbf{W_t} + \alpha_2 \Delta \log \mathbf{X_t} - \alpha_3 \mathbf{\Omega^{nw}} \Delta \mathrm{log} \mathbf{L_t} \tag{A28}$$

where $(\alpha_1, \alpha_2, \alpha_3)$ are functions of the underlying parameters. This can be re-arranged to give the following "reduced form" expression for the change in wages:

$$\Delta \log \mathbf{W_t} = \alpha_2 \left[\mathbf{I} - \alpha_1 \mathbf{\Omega^{nw} \Omega^{nr}} \right]^{-1} \Delta \log \mathbf{X_t} - \alpha_3 \left[\mathbf{I} - \alpha_1 \mathbf{\Omega^{nw} \Omega^{nr}} \right]^{-1} \mathbf{\Omega^{nw}} \Delta \mathrm{log} \mathbf{L_t} \tag{A29}$$

and taking a first order approximation:

$$\Delta \log \mathbf{W_t} \approx \alpha_2 \left[\mathbf{I} + \alpha_1 \mathbf{\Omega^{nw} \Omega^{nr}} \right] \Delta \log \mathbf{X_t} - \alpha_3 \left[\mathbf{I} + \alpha_1 \mathbf{\Omega^{nw} \Omega^{nr}} \right] \mathbf{\Omega^{nw}} \Delta \mathrm{log} \mathbf{L_t} \tag{A30}$$

which is the estimating equation (21) in the text. Note that the parameters $(\alpha_1, \alpha_2, \alpha_3)$ are complicated non-linear functions of the underlying parameters of the model which cannot be separately identified in estimation. The response of wages to demand and population shocks can, however, be identified.

Tables and figures

Table 1: Comparison of British wards and TTWAs and American CZs

Percentiles:	GB Wards			GB TTWAs			US TTWAs		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Land area (km^2)	1	5	53	302	745	1,961	3,315	7815	20,146
Population (000s)	2	4	12	20	120	492	13	94	642
Pop density (residents/km^2)	48	1,117	4,778	22	177	834	2	14	67
Share working in unit of residence									
Pctiles of geographical units	0.11	0.20	0.38	0.67	0.74	0.87	0.83	0.92	0.97
National share	— 0.21 —			— 0.81 —			— 0.94 —		
Employment rate 16-64s									
2011 (UK) / 2010 (US)	0.62	0.68	0.73	0.62	0.67	0.71	0.53	0.60	0.65
1991 (UK) / 1990 (US)	0.59	0.70	0.75	0.62	0.68	0.73	0.60	0.69	0.76
1971 (UK) / 1970 (US)	0.60	0.72	0.77	0.64	0.70	0.75	0.56	0.65	0.77

This table reports percentiles of various statistics across the 9,975 wards and 232 Travel-To-Work-Areas (TTWAs) in our sample, as well as the 722 Commuting Zones (CZs) of the Continental US. Population and density are local means over the full sample, i.e. decadal census observations between 1971 and 2011 inclusive (and 1970-2010 for the US). The share of employed individuals working in their geographical unit of residence (whether ward, TTWA or CZ) is a local mean over 1981-2011 (and 1980-2010 for the US): we do not have British commuting flows for 1971. As well as local percentiles, we report the national share of employed individuals who work in their unit of residence. Employment rates for individuals aged 16-64 are reported separately for different years.

Table 2: Temporal autocorrelations of local employment rate

		Wards: ACF lags				TTWAs: ACF lags			
		1	2	3	4	1	2	3	4
(1)	Basic emp rate	0.760	0.501	0.342	0.250	0.693	0.553	0.370	0.192
	Sub-samples								
(2)	Men	0.782	0.605	0.584	0.541	0.702	0.654	0.635	0.508
(3)	Women	0.718	0.332	0.055	-0.065	0.739	0.453	0.167	-0.012
(4)	Labor force	0.762	0.646	0.690	0.527	0.749	0.698	0.720	0.506
	Microdata								
(5)	Basic emp rate	-	-	-	-	0.848	0.728	0.578	0.221
(6)	Composition-adjusted	-	-	-	-	0.845	0.718	0.557	0.223
	Within-area								
(7)	Unadjusted	0.310	-0.48	-0.733	-0.570	0.106	-0.378	-0.549	-0.589
(8)	Bias-corrected: $\pi = 0.9$	0.842	0.642	0.502	0.451	0.809	0.701	0.603	0.543
(9)	Bias-corrected: $\pi = 0.5$	0.736	0.402	0.168	0.084	0.631	0.423	0.233	0.116
(10)	Bias-corrected: $\pi = 0$	0.711	0.347	0.091	0	0.582	0.347	0.132	0

This table reports autocorrelation functions (ACFs) of the time-demeaned log local employment rate over four decadal lags, based on the full panel between 1971 and 2011 of both wards and TTWAs. The first row presents the basic ACF. Rows 2-4 estimate ACFs for employment rates within various sub-samples. Column 5 reports the ACF for 118 coarser "microdata TTWAs" (whch correspond roughly to groups of TTWAs), as defined in Appendix A.5. In column 6, we use employment rates which are adjusted for observable differences in local demographic composition. Columns 7-10 estimate ACFs for employment rates which are purged of area fixed effects. Columns 8-10 adjust these ACFs for the associated short-panel bias. As the text describes, this requires one identifying assumption: we fix the ratio π of the fourth to third decadal autocorrelation.

Table 3: Model for the cost of commuting d_{ab}

	FE Poisson (1)	FE Poisson (2)	FE Poisson (3)	FE Poisson (4)	Log-Linear (5)	Log-Linear (6)	NLS (7)
Log distance	-1.13***	-0.928***	-0.871***	-0.958***	-2.791***	-2.979***	-0.832***
	(0.027)	(0.0189)	(0.0218)	(0.0217)	(0.00311)	(0.00235)	(0.0003)
Log distance squared	-0.230***	-0.209***	-0.234***	-0.235***	0.280***	0.276***	-0.221***
	(0.005)	(0.00460)	(0.00501)	(0.00502)	(0.000429)	(0.000327)	(0.0001)
Origin fixed effects	Yes	No	Yes	No	No	Yes	No
Destination fixed effects	Yes	No	No	Yes	No	Yes	No
Observations	99.5m	99.5m	99.5m	99.5m	99.5m	99.5m	99.5m

This table reports estimates of equation (12), our model for the computed commuting costs d_{ab} between origin-destination pairs, using various empirical methodologies and fixed effect combinations. Errors are clustered by ward, and robust SEs are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

PANEL A: OLS and IV

	OLS		IV	
	FE	FD	FE	FD
	(1)	(2)	(3)	(4)
Bartik	0.307***	0.177***	0.301***	0.179***
	(0.024)	(0.025)	(0.029)	(0.027)
$\Omega^{nw}\Omega^{nr}$ * Bartik	-0.182***	-0.032	0.320***	0.289***
	(0.070)	(0.068)	(0.108)	(0.088)
Ω^{nw} * Log population	0.939***	1.146***	-3.596***	-2.026***
	(0.085)	(0.088)	(0.253)	(0.183)
$\Omega^{nw}\Omega^{nr}\Omega^{nw}$ * Log population	-0.945***	-1.293***	2.285***	0.907***
	(0.113)	(0.109)	(0.301)	(0.220)
Observations	39,900	29,925	39,900	29,925

PANEL B: First stage

	Ω^{nw}*Log Population		$\Omega^{nw}\Omega^{nr}\Omega^{nw}$*Log Population	
	FE	FD	FE	FD
	(1)	(2)	(3)	(4)
Ω^{nw} * Altonji-Card	1.096***	0.966***	-0.033	-0.244***
	(0.071)	(0.068)	(0.032)	(0.028)
$\Omega^{nw}\Omega^{nr}\Omega^{nw}$ * Altonji-Card	-0.509***	-0.190***	0.756***	1.232***
	(0.076)	(0.063)	(0.037)	(0.028)
Observations	39,900	29,925	39,900	39,900

This table reports estimates of equation (21), our model for local wages. Our dependent variable is local changes in the computed $\log Z_{bt}$: as we show in the text, this corresponds to local wage changes up to a national time effect. The right hand side variables consist of an own-ward Bartik and a double convolution (weighting across neighboring wards, according to the size of commuting flows), as well as a weighted population shock and its corresponding double convolution. We offer both OLS estimates and IV estimates which treat the population shocks as enogenous. Our instruments are the corresponding (weighted) Altonji-Card local migrant shift-shares. We offer both first differenced (FD) estimates, as in equation (21), and also fixed effect (FE) estimates where we cumulate the Bartik shocks and Altonji-Card instruments appropriately. Errors are clustered by ward, and robust SEs are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Determinants of local employment rate

PANEL A: OLS and IV

	OLS				IV			
	FE	FE	FD	FD	FE	FE	FD	FD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inclusive value	0.025***	0.024***	0.014***	0.014***	0.170***	0.226***	0.080***	0.120***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.016)	(0.016)	(0.017)	(0.016)
Log population	-0.026***		-0.001		-0.349***		-0.172***	
	(0.008)		(0.008)		(0.025)		(0.021)	
Observations	39,900	39,900	29,925	29,925	39,900	39,900	29,925	29,925

PANEL B: First stage

	Inclusive Value		Log Population	
	FE	FD	FE	FD
	(1)	(2)	(3)	(4)
Weighted Bartik	0.623***	0.444***	0.172***	0.167***
	(0.048)	(0.050)	(0.018)	(0.017)
Altonji-Card	-1.203***	-0.831***	0.761***	0.686***
	(0.069)	(0.052)	(0.036)	(0.032)
Observations	39,900	29,925	39,900	29,925

This table estimates the OLS and IV response of the local employment rate to the inclusive value (computed using (23)) and the local population shock, based on equation (22). For our IV estimates, we instrument the inclusive value with a commuting-weighted Bartik, and we instrument the local population shock with the Altonji-Card migrant shift share. We offer both first differenced (FD) estimates, as in equation (22), and also fixed effect (FE) estimates where we cumulate the Bartik shocks and Altonji-Card instruments appropriately. Errors are clustered by ward, and robust SEs are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Population responses

PANEL A: OLS and IV

	Ward-level estimates					TTWA-level estimates		
	OLS	IV	IV	IV		OLS	IV	IV
	(1)	(2)	(3)	(4)		(5)	(6)	(7)
Δ log emp	0.899***	0.392***	0.638***	0.879***		0.558***	0.539***	0.671***
	(0.008)	(0.072)	(0.054)	(0.131)		(0.019)	(0.046)	(0.080)
Lagged log emp rate	0.170***	0.519***	0.465***	-0.359		0.213***	0.331***	0.432***
	(0.019)	(0.075)	(0.061)	(0.469)		(0.020)	(0.099)	(0.122)
Ward/TTWA FEs	No	No	Yes	Yes		No	No	Yes
TTWA*yr FEs	No	No	No	Yes		No	No	No
Observations	39,900	39,900	39,900	39,900		232	232	232

PANEL B: First stage for wards

	Δ log emp				Lagged log emp rate		
	(1)	(2)	(3)		(4)	(5)	(6)
Weighted Bartik	0.728***	1.062***	0.751***		-0.176***	0.022	0.068
	(0.098)	(0.154)	(0.153)		(0.036)	(0.050)	(0.044)
Lagged weighted Bartik	0.141	0.127	1.093***		0.853***	1.054***	0.397***
	(0.093)	(0.187)	(0.183)		(0.049)	(0.065)	(0.062)
Ward fixed effects	No	Yes	Yes		No	Yes	Yes
TTWA*yr FEs	No	No	Yes		No	No	Yes
Observations	39,900	39,900	39,900		39,900	39,900	39,900

PANEL C: First stage for TTWAs

	Δ log emp		Lagged log emp rate	
	(1)	(2)	(3)	(4)
Weighted Bartik	0.819***	0.848***	-0.226***	-0.137
	(0.121)	(0.206)	(0.073)	(0.141)
Lagged weighted Bartik	0.069	0.276	0.393***	0.424***
	(0.105)	(0.186)	(0.075)	(0.138)
TTWA fixed effects	No	Yes	No	Yes
Observations	232	232	232	232

Panel A reports estimates of the local population response across both wards and TTWAs, based on equation (25). All specifications are written in first differences, as in (25). In our IV specifications, we instrument the change in log employment with the current commuting-weighted Bartik; and we instrument the lagged employment rate with the lagged weighted Bartik. The corresponding first stages are reported in Panels B and C. In columns 3-4 and 7 of Panel A, we control additionally for local (either ward or TTWA) fixed effects to account for unobserved supply shocks. And in the ward-level specification of column 5, we also control for interacted TTWA-year fixed effects - in order to study population movements within TTWAs. All specifications control for both current and lagged Altoni-Card migrant shift-shares. And in those specifications without fixed effects, we also include time-invariant climate effects: specifically, the number of heating degree days (the average annual number of days with temperature below 15.5°C), cooling degree days (the number of days above 22°C) and rainfall intensity (average precipitation on days when there is more than 1mm). This data was kindly shared by Steve Gibbons, who constructed it from Met Office statistics (Gibbons, Overman and Resende, 2011). Errors are clustered by geographical unit of analysis, and robust SEs are in parentheses. ** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Spatial correlation in shocks: Estimates of Moran's I

	1981-2011	1981-1991	1991-2001	2001-2011	1981-2011
	(1)	(2)	(3)	(4)	(5)
$\Delta \log Z_{bt}$	0.146***	0.248***	0.003	0.107***	0.121***
	(0.005)	(0.007)	(0.002)	(0.005)	(0.005)
Bartik shock: $\Delta log X_{bt}$	0.100***	0.069***	0.137***	0.114***	0.042***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.002)
Weighted Bartik shock: $\Omega^{nw}\Omega^{nr}\Delta log X_{bt}$	0.791***	0.759***	0.813***	0.796***	0.609***
	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Population shock: $\Omega^{nw}\Delta log L_{bt}$	0.533***	0.523***	0.555***	0.520***	0.516***
	(0.010)	(0.015)	(0.019)	(0.008)	(0.011)
Weighted population shock: $\Omega^{nw}\Omega^{nr}\Omega^{nw}\Delta log L_{bt}$	0.886***	0.870***	0.933***	0.839***	0.878***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Composite shock $\alpha_2\left[I+\alpha_1\Omega^{nw}\Omega^{nr}\right]\Delta log X_{bt} - \alpha_3\left[I+\alpha_1\Omega^{nw}\Omega^{nr}\right]\Omega^{nw}\Delta log L_{bt}$	0.234***	0.246***	0.201***	0.260***	0.232***
	(0.007)	(0.011)	(0.012)	(0.007)	(0.008)
Log employment rate	0.399***	0.431***	0.448***	0.320***	0.321***
	(0.011)	(0.007)	(0.013)	(0.014)	(0.014)
Change in log employment rate	0.386***	0.370***	0.358***	0.453***	0.419***
	(0.010)	(0.007)	(0.017)	(0.008)	(0.009)
Ward fixed effects	No	No	No	No	Yes
Observations	29,925	9,975	9,975	9,975	29,925

This table presents estimates of Moran's I for the variable listed in the first column. The weights used are the average commuting flows observed. Errors are clustered by ward (in regressions covering more than one year), and robust SEs are in parentheses. ** p<0.01, ** p<0.05, * p<0.1.

Table 8: Spatial correlation in shocks: Heterogeneity in Moran's I

	$\Delta \log Z_{at}$			Composite Shock		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Moran's I (Main Effect)	0.145***	0.146***	0.145***	0.237***	0.233***	0.236***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Main Effect interacted with 1981 manufacturing share	0.001		0.001	0.051		0.062*
	(0.020)		(0.020)	(0.033)		(0.032)
Main Effect interacted with 1981 log employment rate		0.152***	0.146***		-0.432***	-0.437***
		(0.050)	(0.050)		(0.076)	(0.078)
Observations	29,925	29,925	29,925	29,925	29,925	29,925

This table presents estimates of Moran's I for the variable listed in the first row, and the weights used are the average commuting flows observed. The interaction variables are the main effect multiplied by the deviation of the interacting variable from its mean. The interacting variables themselves are also included as regressors. Errors are clustered by ward, and robust SEs are in parentheses. ** p<0.01, ** p<0.05, * p<0.1.
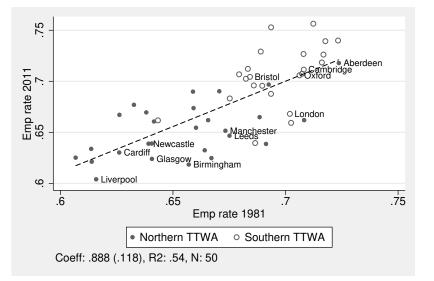
Figure 1: Persistence in employment rates

Note: Data-points denote Travel-To-Work-Areas (TTWAs). Sample is restricted to the 50 largest TTWAs in 1981, for individuals aged 16-64. TTWAs are divided into "North" and "South", where the latter consists of the South West, South East, East of England and East Midlands regions.
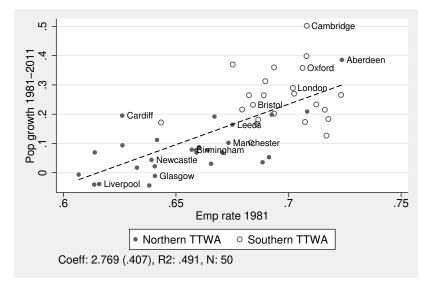

Figure 2: Population response to employment rates

Note: Data-points denote Travel-To-Work-Areas (TTWAs). Sample is restricted to the 50 largest TTWAs in 1981, for individuals aged 16-64.
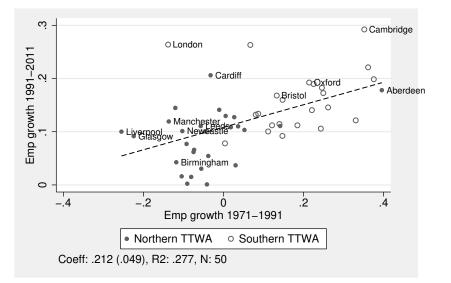
Figure 3: Persistence in local employment growth

Note: Data-points denote Travel-To-Work-Areas (TTWAs). Sample is restricted to the 50 largest TTWAs in 1981, for individuals aged 16-64
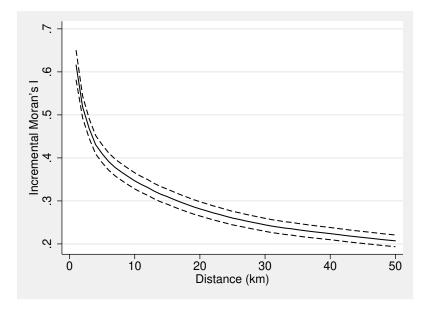

Figure 4: Spatial correlation in change in log employment rates

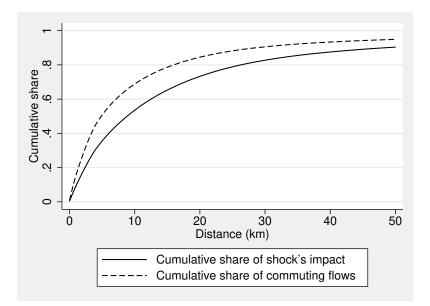Note: Dashed lines represent 95 percent confidence intervals.
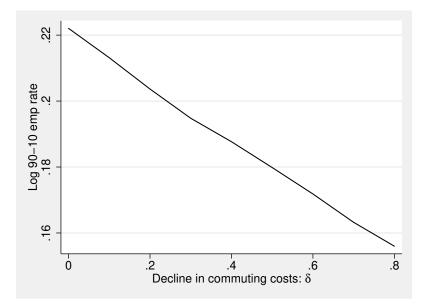
55

Figure 5: Spatial impulse response to local shocks

Figure 6: Impact of commuting costs on spatial employment rate differentials

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