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Why does birthplace matter so much? Sorting, learning and geography[*]

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Abstract: We consider the link between birthplace and wages. Using a unique panel dataset we estimate a raw elasticity of wage with respect to birthplace size of 4.6%, two thirds of the 6.8% raw elasticity with respect to city size. We consider a number of mechanisms through which this birthplace effect could arise. Our results suggest that inter-generational transmission (sorting) and the effect of birthplace on current location (geography) both play a role in explaining the effect of birthplace. We find no role for human capital formation at least in terms of educational outcomes (learning). Our results highlight the importance of intergenerational sorting in helping explain the persistence of spatial disparities.

Key words: place of birth, spatial sorting, lifetime mobility

JEL codes: J61, J62, R23, J31

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1. Introduction

The question of links from birthplace to outcomes has long been a concern of the neighbourhood effects literature that looks at the impact of growing up in a disadvantaged neighbourhood on individual outcomes (see e.g. Oreopoulos, 2003; Durlauf, 2004; Topa and Zenou, 2014; Chetty et al., forthcoming). Our work asks a similar question, but at a larger spatial scale (the local labour market rather than the neighbourhood). It contributes to a small, but growing literature that considers the impact of 'initial conditions' in determining labour market outcomes (see e.g. Aslund and Rooth, 2007; Almond and Currie, 2011). Our emphasis on birthplace and intergenerational sorting means the paper is also related to recent works on the geography of intergenerational mobility (Chetty et al., 2014; Chetty and Hendren, 2015) and highlights, in a different manner and at a different spatial scale, that there is a geographic component to the inheritance of inequality.[1]

We focus on the impact of birthplace size using a unique panel data set (the British Household Panel Survey) which provides information on wages, current location *and* birthplace for a sample of UK individuals and households questioned annually between 1991 and 2009.[2] We estimate a raw elasticity of wage with respect to birthplace size of 4.6%, two thirds of the 6.8% raw elasticity with respect to city size. The BHPS also provides information on individual characteristics and a limited set of parental characteristics which allows us to consider the mechanisms through which this effect occurs.

Why could birthplace size matter? One possibility is that individual characteristics vary with birthplace size because of the spatial sorting of parents and the intergenerational transmission of characteristics ('sorting'). A second possibility is that birthplace size affects the accumulation of human capital – for example because the quality of schools varies with city size ('learning'). A third possibility is that birthplace influences migration and choice of labour market – and, thus, that the effect of birthplace size captures differences in labour market opportunities that in turn depend on size of city of birth ('geography').[3] Indeed, in the extreme case of no mobility, birthplace size directly determines labour market size and it makes little sense to try to distinguish between the effect of birthplace and current location. We consider all three of these possibilities in the paper. We also consider whether other city

[1] An idea that is mentioned, but not studied, by Bowles and Gintis, 2002.

[2] After cleaning, the panel provides information on a little over 7,000 workers. Given the size of the panel, we follow the agglomeration literature and focus on the link from city size – both birthplace and current location – to wages, rather than on fully characterising the set of area effects.

[3] The terminology we use here – sorting, learning and geography - was introduced by Glaeser and Maré, 2001.

attributes – specifically current and birthplace unemployment – have an effect on wages in addition to the birthplace and current city size effects.

Our paper is closely related to the literature that considers the extent of spatial disparities and the role of agglomeration economies in explaining these disparities. In the urban economics literature it is increasingly recognised that sorting – the concentration of more productive workers in more productive locations – plays an important role in understanding disparities across space. For example, Combes et al. (2008) show that, for wages in France, the correlation between average individual fixed effects and area fixed effects is somewhere around 0.3. Mion and Naticchioni (2009) find qualitatively similar results for Italy. Such positive correlation can explain a large part of overall spatial disparities. For example, Gibbons et al. (2014) show that between 85% and 88% of area wage disparities in the UK are explained by individual characteristics (including individual fixed effects). Combes and Gobillon (2015) provide a recent survey and further discussion.

Because this literature uses individual level panel data to estimate area effects from movers across areas, there is a tendency to assume that the 'sorting' that explains the concentration of more productive workers in more productive locations is predominantly driven by the mobility decisions of workers. However, it is equally possible that the sorting that explains this concentration is predominantly the result of birthplace effects on individual characteristics combined with low levels of mobility. Indeed, both Mion and Naticchioni (2009) and Combes et al. (2012) show that selective migration accounts for little of the skill differences between dense and less dense areas, and suggest a role for 'sorting at birth'. These birthplace effects could occur directly (e.g. if birthplace size helps determine educational outcomes) or indirectly via the sorting of parents (e.g. if parental characteristics help determine educational outcomes and parental characteristics are correlated with city size). In this scenario, more productive areas tend to generate more productive workers and the sorting of adult workers simply serves to reinforce this concentration. This paper attempts to distinguish between these possibilities by looking at the role of sorting, learning and geography in explaining the birthplace effect.

As in the neighbourhood effects and agglomeration literatures, in the absence of random allocation of families and individuals across locations, our estimates of birthplace effects need careful interpretation. In particular, it is difficult to separate out the causal effect of birthplace from the effects of family characteristics when families with different characteristics are spatially concentrated in different areas. Our data allows us to make some progress in this regard by controlling for a narrow set of parental characteristics that are available for a proportion (75%) of the panel. Exploiting the panel dimension of the data, we are also able to consider the extent to which mobility helps explain the role of birthplace.

Our results suggest that inter-generational transmission (sorting) and the effect of birthplace on current location (geography) both play a role in explaining the effect of birthplace. We find no role for human capital formation, at least in terms of educational outcomes, but we find some cumulative effect of geography through accumulated experience in big cities (i.e. adult rather than childhood learning). This highlights the importance of intergenerational sorting in helping explain the persistence of spatial disparities. Low lifetime mobility reinforces the link between the location decisions of generations, which suggests that there is a geographic component of inequality at birth in addition to intergenerational transmission through parental characteristics. We provide descriptive evidence on lifetime mobility that suggests this is an important consideration in the UK: in our data around 43.7% of individuals only ever work while living in the same area as they were born.

The rest of the paper is structured as follows. The next section outlines our data and provides basic summary statistics. Section 3 presents the econometric strategy while Section 4 describes our main findings. Section 5 explores possible mechanisms in more depth. Finally, Section 6 concludes.

2. Data and descriptive statistics

We use the British Households Panel Survey (BHPS) which is a non-balanced panel of households/individuals questioned in 18 waves from 1991 to 2009. The BHPS is based on a nationally representative sample of households recruited in 1991. Panel members comprise all individuals resident at sampled addresses at the first wave of the survey. Subsequent surveys re-interview these individuals annually, following any individuals who split-off from original households (e.g. because of family break-up or because a child enters adulthood and leaves home). All adult members of new households are interviewed, as are new members joining sample households. Children are interviewed once they reach the age of 16. The panel has a number of advantages. In addition to being representative, it also provides both labour market and geographical information (including birthplace) at a fine level of detail for individuals observed over a relatively long period of time.[4]

The full sample consists of 32,380 individuals observed on average 7.4 times for a total of 238,996 observations. Available variables cover a variety of topics including education, labour market outcomes, income, health, personal values, labour and life conditions (e.g. workplace characteristics, union membership, family commitments, relationship status, wellbeing), etc. In terms of outcome variable, we focus on total gross pay constructed from self-reported data on 'usual gross pay per month in current job'. Basic control variables – gender and age – are available for all individuals. For parental characteristics we use a measure of social class based on self-reported parental occupations ranging from unskilled to professional occupation with the parents' highest social class constructed as the maximum rank of mother and father.[5] For individual educational outcomes we construct a measure of qualification based on reported highest educational and academic qualifications. We end up with seven educational dummies: no qualifications; apprenticeship; GCSE; A-level; HNC, HND, or teaching qualifications; 1st degree and higher degree.[6] These are mapped to years of education based on the modal education leaving age for each category. We also have information on the individual's current occupation classified according to one-digit SOC (standard occupational classification, see Appendix C for details).

In addition to information on these family and individual characteristics, the data set also provides information on both place of residence and birth. For place of residence we have very precise geographical coordinates (eastings and northings), while place of birth is recorded at the Local Authority level. To study spatial sorting across cities we follow much of the existing literature, and map these two geographies to local labour markets.[7] Given sample sizes, and because providing birthplace coefficients for 142 local labour markets would not be particularly informative, we focus on the effect of birthplace and current city sizes.[8] One

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[4] More details on the BHPS can be found here: https://www.iser.essex.ac.uk/bhps.

[5] From the lowest to the highest social class the categories of occupation are as follows: unskilled, partly skilled, skilled manual, armed forces, skilled non-manual, managerial and technical, and professional occupations.

[6] GCSEs are usually taken at the end of compulsory schooling (age 16). They replaced O-levels and CSE (we count these all as one category); A-levels are usually taken at the end of schooling (age 18). HNC is a Higher National Certificate, usually involving one year's study post-18 while HND is a Higher National Diploma usually involving two years study post-18. Most UK 1st degrees involve three years post-18 study.

[7] Local labour markets have been merged from Travel-to-work areas; see Gibbons et al. (2014) for details.

[8] Birthplace and current city sizes, defined as the number of people in employment, as well as unemployment rates are matched from the closest census year (1971, 1981, 1991, 2001 and 2011), see Appendix B for local labour market size and unemployment rates at these dates. Results available on request show that all results in the paper are robust to matching to specific years with linear interpolations between census years.

disadvantage of the data is that we only have information on where people live, rather than where they work. This is unfortunate, because the existing agglomeration literature is mainly concerned with the link from work place size to wages. In practice, this is not a major problem because Travel to Work Areas, our underlying geography, are constructed to maximise the percentage of individuals who both live and work in the same area. Consistent with this, as we report below, we get estimates of the elasticity of wages with respect to current city size that are broadly in line with the existing literature.

Given small sample sizes, we drop individuals who were born outside of Great Britain (including those born, or currently located, in Northern Ireland). As our main focus is on wage disparities, we also drop observations corresponding to years in which the individual is studying, unemployed or retired. Concerns over self-reported hours lead us to focus on the total wage for full-time workers.[9] To allow us to include a reasonable set of observable characteristics, we drop individuals with missing occupation, education and parents' highest social class.[10] This leaves us with 57,101 observations for 9,153 individuals. Finally, when using the panel dimension of the data (with individual fixed effects), we keep only workers observed at least twice. This leaves us with 55,357 observations for 7,500 individuals. This is our minimum sample size although, as will become clear below, we can use larger samples in some of our estimations when the full set of restrictions need not apply.

Descriptive statistics are provided in Table 1. Column (1) presents descriptive statistics for the sample of full-time workers restricted on the basis of country of birth (dropping those born outside Great Britain, including in Northern Ireland) and dropping individuals who are studying, unemployed or retired. The focus on full time workers leads to women being slightly under-represented in the total sample. Gross (monthly) pay figures deflated to 2005 base year look broadly in line with those reported from the Annual Survey of Hours and Earnings (and before that from the New Earnings Survey). Average city size is larger for birthplace than for current residence – explained by our focus on natives/individuals born in Great Britain (immigrants tend to live in larger cities: in the BHPS, 3.1% of individuals living in rural areas are born abroad against 7.1% for individuals living in urban areas and 20% for individuals living in London). Column (2) shows what happens when we drop individuals with missing education, column (3) additionally drops those with missing occupation and

[9] Results available on request show that our findings are robust to considering all workers (including part time).

[10] For observations with missing data for these variables, we extrapolate or interpolate from existing data where appropriate.

column (4) those with missing parent's highest social class. Finally, column (5) keeps only full-time workers observed at least twice – the sample that we use when including fixed effects to exploit the panel dimension of the data. As is to be expected, these restrictions slightly skew the sample towards those with higher incomes and occupations associated with higher education levels – particularly when dropping individuals with missing highest parent social class and individuals observed only once. But none of the changes are particularly large. In short, to the extent the initial sample is representative, restricting on observable characteristics does not significantly affect the representativeness of our final sample.

Table 1: Descriptive statistics for full-time workers

Variable	(1)	(2)	(3)	(4)	(5)
Women (%)	46.0	46.1	46.1	45.9	44.7
Age	34.9	34.7	34.7	37.5	38.2
Gross pay	1,487	1,490	1,490	1,586	1,649
Occupation (%)					
Managers / Senior Officials	14.1	14.1	14.1	15.3	16.1
Professional Occupations	9.7	9.9	9.9	10.9	11.5
Professional & Technical	11.6	11.6	11.6	12.3	12.7
Admin & Secretarial	17.8	17.9	17.9	17.5	17.1
Skilled Trades	11.7	11.7	11.7	11.2	11.3
Personal Service	11.3	11.2	11.2	10.3	9.7
Sales and Customer Service	6.6	6.6	6.6	5.7	5.4
Machine Operatives	10.5	10.3	10.3	10.6	10.4
Elementary	6.7	6.6	6.6	6.2	5.7
Location					
Resident city size	504,919	507,543	507,732	488,439	475,579
Live in city (%)	70.6	70.6	70.7	69.6	69.6
Live in London (%)	7.8	7.9	7.9	7.5	7.1
Birth city size	587,010	585,844	585,404	596,331	603,166
Born in city (%)	75.0	74.9	74.9	74.2	74.4
Born in London (%)	9.4	9.4	9.4	9.5	9.7
Number of observations	72,565	70,026	70,006	57,101	55,357
Number of individuals	12,699	12,370	12,364	9,244	7,500

Source: Authors own calculation based on BHPS. Notes: Gross pay data are monthly and have been deflated using a consumer price index (base year = 2005). Occupations classified according to one-digit SOC.

3. Econometric strategy

We now outline the way in which we estimate the effect of both current location and birthplace on individual wages. Given sample sizes, our focus is on estimating the effect of city size, rather than the full set of birthplace and current city effects.[11]

Denote (the log of) wage of individual i living in area a at date t as $w_{i(a)t}$. A simple 'one-step' method for assessing how outcomes vary with birthplace size is to regress

$$w_{i(a)t} = \gamma BP_i + \varepsilon_{i(a)t} \tag{1}$$

where BP_i is the (log of) birthplace size (calculated as described in Section 2) and γ captures the elasticity of wage with respect to birthplace size. As discussed in the introduction, the coefficient on BP_i captures both the direct impact of birthplace size and the effect of any family characteristics that are correlated with BP_i. Data on parental characteristics allows us to partially control for this second channel, as in the neighbourhood effects literature, by estimating:

$$w_{i(a)t} = \gamma BP_i + \rho PX_i + \varepsilon_{i(a)t} \tag{2}$$

where PX_i are parental characteristics and ρ is a vector of coefficients. Unfortunately, we have relatively limited data on parental characteristics – controlling for these reduces, but almost certainly does not fully eliminate, the effect of variation in family characteristics that is attributed to BP_i.

We can next add individual observed characteristics to see the extent to which any effect of BP_i works through these observed characteristics. That is, we can estimate:

$$w_{i(a)t} = \gamma BP_i + \rho PX_i + \beta' X_{it} + \varepsilon_{i(a)t} \tag{3}$$

where X_{it} are time varying individual characteristics and β is a vector of coefficients. Given the link from birthplace to childhood conditions for most of the sample (which we document below), it is of particular interest to consider educational outcomes. For individual characteristics, this will be our main focus in what follows.

[11] The mean number of workers by area and year is 38.6 (with a standard deviation of 54.9). For full time workers the mean is 22.4 (s.d. 31.4) if we drop those missing education, occupation, Highest Parental Social Class and birthplace. As should be clear from comparing the mean and standard deviation we have quite a lot of locations with small numbers of observations on an annual basis.

So far, we have introduced controls for parental and individual characteristics, both of which may be correlated with birthplace size. Evidence of low childhood mobility justifies a focus on educational outcomes that may be influenced by childhood conditions. More generally, low lifetime mobility rates also suggest that birthplace can influence labour market outcomes to the extent that it determines place of work. To consider this possibility, we can add in a variable to capture the effect of the size of place of residence. That is, we can run the regression:

$$w_{i(a)t} = \gamma BP_i + \rho' PX_i + \beta' X_{it} + \lambda RP_{i(a)t} + \varepsilon_{i(a)t} \tag{4}$$

where $RP_{i(a)t}$ measures the (log of) size of the current place of residence and λ captures the elasticity of wage with respect to current city size.

While this 'one-step' estimator is intuitive, it leads to inconsistent estimates of $\gamma, \rho, \beta\ \lambda$, once we allow for the possibility that individual unobserved characteristics may be correlated with current city size. Even if these individual unobserved characteristics are uncorrelated with birthplace size (after conditioning on parental characteristics) any correlation between current city size and birthplace size will still render estimates of γ inconsistent. More formally, assume that the equation for wage $w_{i(a)t}$ is:

$$w_{i(a)t} = \eta_i + \gamma BP_i + \rho' PX_i + \beta' X_{it} + \lambda RP_{i(a)t} + \varepsilon_{i(a)t} \tag{5}$$

where η_i is some time invariant individual unobserved characteristics (e.g. ability) then even if $E[\eta_i | BP_i, PX_i, X_{it}] = 0$, so that BP_i and η_i are uncorrelated conditional on parental and individual characteristics, inference based on:

$$w_{i(a)t} = \gamma BP_i + \rho' PX_i + \beta' X_{it} + \lambda RP_{i(a)t} + \varepsilon_{i(a)t} \tag{6}$$

is biased because $E[RP_i | BP_i] \neq 0$ (due to low lifetime mobility) and $E[\eta_i | RP_i] \neq 0$ (due to spatial sorting on unobserved individual ability).

To overcome this problem, we adopt a two-step econometric strategy in the same spirit as Combes et al. (2008). In the first step, we regress wages of individual *i* living in area *a* at date *t* on an individual fixed effect θ_i, time-varying observable characteristics X_{it}, an area size effect $RP_{i(a)t}$, and a time fixed effect δ_t:

$$w_{i(a)t} = \theta_i + \beta' X_{it} + \lambda RP_{i(a)t} + \delta_t + \varepsilon_{i(a)t} \tag{7}$$

In the second step, we then regress the estimated individual fixed effects on time-invariant characteristics including birthplace:

$$\hat{\theta}_i = \gamma BP_i + \alpha' Z_i + \eta_i \quad (8)$$

where Z_i includes gender, education and parental characteristics, and α is the corresponding vector of coefficients.

Following the literature, assuming that time variant unobserved shocks are uncorrelated with $RP_{i(a)t}$, we can use the panel dimension of our data to estimate (7) to provide a consistent estimate of the coefficient on $RP_{i(a)t}$. If we also assume that $E[\eta_i | BP_i, PX_i, X_{it}] = 0$ then this two-step procedure also provides us with consistent estimates of the effects of birthplace and parental characteristics.

It is important to note, however, that if we were interested in identify the overall *causal* effect of birthplace size, education and parents' social class may be considered bad controls if they are correlated with birthplace size. In particular, if birthplace size has an effect through individual education or occupation, controlling for education or occupation will lead us to underestimate the total effect of birthplace size. In contrast, spatial sorting of parents based on unobservable characteristics might lead us to put too much weight on birthplace. Fortunately, our ambitions are more modest – we are interested in understanding the link between wages and birthplace size and the possible mechanisms that might explain this, but we do not claim to estimate a causal effect of birthplace size. Nevertheless, when we consider the results below we will always be interested in the coefficients on birthplace size both with and without the control covariates.

In a recent paper, De la Roca and Puga (2014) suggest that we should be careful to distinguish between static and dynamic agglomeration economies when estimating wage equations of the kind we use in our first step (i.e. equation (7)). If adult learning is important, De la Roca and Puga show that we should control for the whole labour market history when assessing the impact of current city size. In their estimation, they consider a full set of area effects so allowing for the effect of adult learning involves the introduction of city-specific experience variables in their estimated equation. In our specification with only city size on the right hand side, this equates to including a variable that captures accumulated city size (up to and including the period before the current observation) in the first-step estimation. That is, we can estimate:

$$w_{i(a)t} = \theta_i + \beta' X_{it} + \lambda RP_{i(a)t} + \theta \sum_{t=t_0}^{t-1} RP_{i(a)t} + \varepsilon_{i(a)t} \tag{7a}$$

where the summation captures accumulated city size from the time that the individual entered the labour market (t_0) until the period before the current observation. Following De-la-Roca and Puga, we restrict the summation to periods where the individual is working so that it has the interpretation of accumulated experience.[12]

We present results using both the static and dynamic first-step specifications in what follows. As we discuss further below, once we recognise that birthplace size can be important, and that mobility rates are low, this further increases the difficulty of separately identifying the effect of current city size from accumulated experience.

4. Results

We start with the more intuitive one-step specification which provides some preliminary evidence on the effect of birthplace size. Results from regressions of wages on birthplace size (plus controls) are reported in Table 2.[13] As both wages and birthplace size are in logs, the coefficients have the standard interpretation as elasticities of wage with respect to birthplace size. Results in column (1) with basic controls for gender, age and age squared suggest that a doubling of birthplace size leads to a 3.8% increase in wages (for those working full time). Adding controls for parental social class (column 2) reduces the coefficient on birthplace size. But conditional on parental social class, controlling for education (column 3) has no impact on the birthplace size elasticity. Finally, controlling for occupation (column 4) further reduces the coefficient on birthplace size (by similar orders of magnitude to the change when introducing parental social class). As discussed above, if we think that education and occupation are in fact determined by birthplace size then these constitute bad controls and we should prefer the estimates in column (1) that control only for gender and age. This suggests that the elasticity of wages with respect to birthplace ranges from around 2.6% to 3.8%. As we will see below, the two-step estimates which correct for the sorting by adults across labour markets show that these one-step coefficients are downward biased.

[12] Results available on request show that our main findings are robust to considering all the time spent by an individual in a city whether working or not.

[13] Results available on request show that these findings are robust to considering all workers, only estimating on lifetime movers, trimming top and bottom 1% of wages, only estimating on workers born 1966 onwards (to allow for the fact that our city size and unemployment data begin in 1971 and that we match workers to the nearest census year) or with linear interpolation between census years. Estimations using birthplace fixed effects yield slightly higher R-squared.

Table 2: One-step regressions of (log) gross total wage on birthplace size and controls (full time workers only)

	(1)	(2)	(3)	(4)
(log) Birthplace size	0.038***	0.032***	0.031***	0.026***
	(0.004)	(0.004)	(0.004)	(0.004)
Time FE	X	X	X	X
Gender, Age, Age2	X	X	X	X
HPSC		X	X	X
Education			X	X
Occupation				X
Observations	57,101	57,101	57,101	57,101
R-squared	0.271	0.312	0.422	0.495
Within time-R2	0.164	0.212	0.337	0.421

Source: Authors own calculation based on BHPS. Notes: Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Education is defined using seven educational dummies, while occupation uses nine dummies based on one-digit standard occupational classification. HSPC is Highest Parental Social Class. See Section 2 for further details.

Before turning to the two-step results for the effect of birthplace size, Table 3 reports results for standard agglomeration regressions where we regress wages on residence, rather than birthplace, size.[14] These results are interesting in two regards. First, because they provide an estimate of the elasticity of wages with respect to city size based on our BHPS data. Second, because they constitute the first-stage estimates that we use in our two-step analysis.

The estimate of the elasticity of wages with respect to city size is around 6.8% when we control only for gender and age, falling to 4.5% as we add individual level controls for, education (column 2) and occupation (column 3). Results reported in column (4) show that this coefficient is roughly halved once we use the panel dimension of our data and include individual fixed effects. Both the point estimates, and the changes in coefficients as we include observable and unobservable characteristics, are broadly in line with the findings from the existing agglomeration literature.[15]

Column (5) shows what happens when we follow de la Roca and Puga (2014) and distinguish between static and dynamic agglomeration economies, by including variables to capture

[14] Results available on request show that these findings are robust to considering all workers, the reduction of the sample to lifetime movers, when dropping London, trimming top and bottom 1% of wages, only estimating on workers born 1966 onwards (to allow for the fact that our city size and unemployment data begin in 1971 and that we match workers to the nearest census year), with linear interpolation between census year and to the reduction of the sample to individuals for whom we observe birthplace.

[15] This is reassuring given that our measure of city size is constructed on the basis of place of residence rather than employment. See section 2 for further discussion.

accumulated experience.[16,17] We hold off on a comparison of the elasticities with respect to birthplace and city size until we have more consistent estimates of the former.

Table 3: First-stage regressions of (log) gross total wage on city size and controls (full time workers only)

	(1)	(2)	(3)	(4)	(5)
(log) City size	0.068***	0.048***	0.045***	0.026***	0.007**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Learning					0.064***
					(0.003)
Time FE	X	X	X	X	X
Gender, Age, Age^2	X	X	X	X	X
Education		X	X	X	X
Occupation			X	X	X
Individual FE				X	X
Observations	77,403	77,403	77,403	77,403	65,311
R-squared	0.324	0.447	0.513	0.855	0.859
Number of ind.	13,725	13,725	13,725	13,725	10,936

Source: Authors own calculation based on BHPS. Notes: Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Learning is (log) accumulated city size as explained in the text. Education is defined using seven educational dummies, while occupation uses nine dummies based on one-digit standard occupational classification (SOC). See Section 2 for further details. For specifications in columns (4) and (5) gender, age and education are time invariant and absorbed by the individual fixed effect.

To obtain these, we switch to two-step estimation. As explained in Section 3, while the one-step results are easy to interpret, estimates of the birthplace city size effect are biased if unobserved ability is correlated with birthplace city size either as a result of low lifetime mobility or because individuals sort on unobserved ability. Switching to two-step estimation allows us to (partially) address this concern subject to the caveats discussed in Section 3.

As a reminder, in the first step, we regress wages on individual fixed effects and a number of time-varying individual observable characteristics that may be correlated with current place of residence. In the second step, we then regress these estimated individual fixed effects on birthplace size – as well as on other time-invariant family and individual characteristics that

[16] We get very similar results when estimating the specification in column (5) using an alternative definition of learning constructed as accumulated city size, whether or not the individual is working. Using this alternative definition, with 68,085 observations on 11,619 individuals we get a coefficient on city size of 0.015 (s.e. 0.003) and on learning of 0.050 (s.e. 0.004). The R-squared is essentially unchanged at 0.856.

[17] The number of individuals is smaller because learning is accumulated city size until t-1, so (with individual fixed effects) we need to observe individuals at least 3 times for them to be included in the sample used to estimate the specification in column (5). We also lose the first observation for these individuals as, by definition, learning is not defined in the first period in which the individual is observed. Results available on request show that columns (1) to (4) are robust to the restriction of the sample to observations for which learning is observed.

may be correlated with birthplace size.[18] Results for the first-stage regressions have already been reported in Table 3, whilst results for the second-stage are reported in Table 4.[19] Comparing column (4) in Table 4, with columns (4) in Table 2 shows that we underestimate the impact of birthplace size if we ignore the correlation between unobserved ability and current city size.

Table 4: Second-stage regressions for gross total wage; individual fixed effects on birthplace and controls (full time workers only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(log) Birthplace size	0.046***	0.040***	0.039***	0.038***	0.028***	0.024***	0.009*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
1st-step controls							
Time FE	X	X	X	X	X	X	X
Occupation				X	X	X	X
(log) City size					X	X	X
Learning							X
2nd-step controls							
Gender, Age	X	X	X	X	X	X	X
HPSC		X	X	X	X	X	X
Education			X	X	X	X	X
Observations	7,500	7,500	7,500	7,500	7,500	4,393	3,839
R-squared	0.140	0.193	0.325	0.308	0.305	0.297	0.300

Source: Authors own calculation based on BHPS. Notes: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. City size is current city size; learning is (log) accumulated city size as explained in the text. Age is average age (see footnote 16). Education is defined using seven educational dummies, while occupation uses nine dummies based on one-digit standard occupational classification (SOC). HSPC is Highest Parental Social Class. See Section 2 for further details. For these second stage estimates the number of observations corresponds to the number of individuals because the dependent variable is the individual fixed effects estimated in the first stage.

Results in Table 4 also allow us to consider how different mechanisms explain the correlation between birthplace size to wages. We start by including controls for parental social class – a

[18] We put time varying variables – time fixed effects, occupation, current and accumulated city size (learning) in the first stage. Time invariant variables – gender, highest parent social class (HSPC) and education go in the second stage. We also control for average age in the second stage because the effect of age cannot be identified with individual and time fixed effects in the first stage (for simplicity we also drop terms in age squared). Average age in the second stage captures both a cohort effect and the fact that more experienced individuals earn higher wages on average. Both effects are not separately identifiable because we observe age and not experience in our data.

[19] Results in Appendix Table A1 show that these findings are robust to only estimating on lifetime movers. Results available on request show that these findings are robust to considering all workers, dropping London, only estimating on workers born 1966 onwards (to allow for the fact that our city size and unemployment data begin in 1971 and that we match workers to the nearest census year), with linear interpolation between census year, to the order of introduction of control variables and using WLS with inverse of individual fixed effects' variance as weights. They are also robust to using an alternative definition of learning constructed as accumulated city size, whether or not the individual is working (see also footnote 18). Estimations using birthplace fixed effects yield slightly higher R-squared. Results available on request show that columns (1) to (6) are robust to the restriction of the sample to individuals for whom learning is observed in the first stage.

family characteristic that is clearly pre-determined for individuals in the sample used for estimation. Results are reported in column (2) and show that the effect of birthplace size is reduced by around 20%, reflecting the fact that some of the correlation between birthplace size and wages is explained by the sorting of *parents* across places of different sizes.[20] Column (3) shows what happens once we introduce individual education as an additional control. The coefficient on birthplace size is almost unchanged, suggesting that the correlation between birthplace city size to wages does not work through own educational outcome (once we control for parental characteristics). Controlling for own occupation (column 4) similarly has little effect.[21] In contrast, controlling for current city size (column 5) has a substantial impact on the birthplace effect reducing it further from 3.8% to 2.8%.

Results so far suggest that the link from birthplace size to wages is partly the result of two mechanisms. First, parental sorting means that educational outcomes differ with birthplace size. Second, birthplace size determines current city size and, as is well known, current city size increases wages as a result of agglomeration economies.

In the last two columns of Table 4 we allow for adult learning by introducing cumulated experience. We focus on 'lifetime movers' (i.e. workers who move at least once during the sample period), because for workers who do not move from their original birthplace it is impossible to separate out the effect of birthplace from the cumulated effect of city size.[22] Column (6) demonstrates that results for the specification reported in column (5) are similar when we only estimate using lifetime movers.[23] As is clear from results in column (5) of Table 3, allowing for learning makes a big difference in terms of the estimated effect of current city size on wages. In turn, this makes a big difference to our estimates of the effect of birthplace size, as shown in the second-stage results reported in the last column of Table 4. This suggests a third mechanism through which birthplace size operates: specifically, it determines the amount of time spent in large cities which increases wages via the effect of adult learning in big cities.

[20] A Wald test suggests that the change in coefficient from 0.040 (0.004) to 0.046 (0.004) is statistically significant.

[21] As with current city size, occupation can be time-varying because some individuals switch occupations, which is why we include the corresponding dummy variables in the first-stage estimation.

[22] For individuals who have never moved from their birthplace, cumulative city size equals age times birthplace size. The only thing that prevents this from being perfectly correlated with age is time series variation in city size which is itself too low to allow identification.

[23] Results available on request show that for this sub-sample of lifetime movers, estimates of the agglomeration elasticity of wages are very similar to those that we obtain with the full sample as reported in Table 3. In this sense, at least, the sub-sample of movers is representative of the broader sample.

To summarise, results so far suggest an elasticity of wages with respect to birthplace size of around 4.6%. The sorting of *parents* across places of different sizes explains some of this correlation. Once we control for this parental sorting, own educational outcome does not play much of a role in explaining the effect of birthplace, and neither does occupation. In contrast, the fact that birthplace size determines current city size plays an important role via the effect of static and dynamic agglomeration economies on wages. We now consider a number of these mechanisms in more detail.

5. Mechanisms

5.1. Parental sorting

We start with the role of parental sorting. As we saw in Table 4, adding controls for parental social class reduces estimates of the elasticity of wages with respect to birthplace size from 4.6% to 4.0%. Given what we know about intergenerational transmission (see, e.g., Black and Devereux, 2011 for a review), this suggests that parental social class must be positively correlated with city size. Table 5 shows a number of descriptive statistics that suggest that this is indeed the case. The first two columns show the percentage of our sample born in a city[24] or in London for workers disaggregated by highest parental social class (HPSC), while the third column shows the average birthplace size similarly disaggregated. Comparing the first and final rows of the table we see that 79.3% of those with professional occupation as the HPSC were born in a city, as opposed to 71.7% for those with unskilled parents. The same figures for London are 12.4% and 6.5%, respectively. In line with this, there are very marked differences for birthplace size. The average birthplace size for a person born to parents with a professional occupation is around 705,000 nearly 50% larger than the average birthplace size for a person born to unskilled parents. The table shows that these differences are much less marked within the three higher social classes (professional, managerial and skilled non-manual) and the four remaining social classes. The differences between those two groupings are, however, pretty marked and underpin the effect of social class on HSPC that we documented above.

[24] We use the same urban/rural classification as Gibbons et al. (2014).

Table 5: Descriptive statistics of birthplace by HPSC

HPSC	Born in city (%)	Born in London (%)	Birthplace size
Professional occupation	79.3	12.4	705,427
Managerial & technical	74.0	10.7	643,377
Skilled non-manual	79.4	12.0	700,114
Armed forces	71.4	10.7	605,948
Skilled manual	72.6	8.6	565,199
Partly skilled occupation	69.0	7.2	503,401
Unskilled	71.7	6.5	476,750
Total	74.0	9.7	604,608

Source: Authors own calculation based on BHPS. Notes: Sample: is non-Northern Ireland, non-students, non-retired for whom we observe both birthplace and HPSC (13,734 individuals). HPSC is Highest Parental Social Class. See Section 2 for further details.

5.2. Education

We next look in more detail at the role of individual education. So far, we have implicitly assumed that birthplace is also the place in which individuals receive their schooling. Table 8 (in the next section) shows that this is a reasonable assumption for more than half our sample. The figures show that at the end of compulsory schooling (16 years old) roughly 60% of individuals live in the same places as they were born. This falls slightly to a little under 56% by the end of schooling (18 years old). These percentages are quite large, but the fact that individuals move during childhood urges some caution in interpreting the link between birthplace size and education as accurately estimating the link between childhood city size and education. Childhood mobility means that birthplace size is not a precise measure of the size of the city in which individuals grow up and this measurement error will tend to attenuate estimates of the effect of birthplace size on educational outcomes. That said, the correlation between birthplace size and city size at ages 16 or 18 is very high (even for movers) which suggests that our estimates of birthplace effects are likely reasonable estimates for childhood city size.[25]

To consider this mechanism further we look directly at the link between education and birthplace size using a measure of years of education (constructed from highest educational and academic qualifications described in Section 2). Table 6 shows results from regressions of

[25] The correlation coefficients between birthplace size and city size at ages 16 and 18 are 0.97 and 0.96, respectively.

this measure of years of education on birthplace size plus controls.[26] Controlling for gender and the year of birth, results in the first column show that there is a positive significant effect of birthplace size on years of education. As we know that years of education are positively correlated with wages (see, e.g, Card, 1999; Harmon et al., 2003 for reviews), this provides one mechanism through which birthplace affects wages.

Note, however, that just as with the neighbourhoods effect literature, the effect of birthplace on education could be picking up either a direct effect of area on education, or an indirect effect of area working through the sorting of families, documented above. Results in columns (2) and (3) of Table 4 already suggested that the effect works through sorting of families. Results in the second column of Table 6 confirm this finding. Once we control for parental social class (in column 2) birthplace size has no effect on years of education. At least for educational outcomes, parental characteristics, rather than birthplace size, explains the positive effect of birthplace size.

Table 6: Regressions of years of education on birthplace and controls

	(1)	(2)
(log) Birthplace size	0.070***	0.023
	(0.018)	(0.017)
Gender	X	X
Year of birth	X	X
HPSC		X
Observations	13,354	13,354
R-squared	0.070	0.172

Source: Authors own calculation based on BHPS. Notes: Sample is non-Northern Ireland, non-students, non-retired for whow we observe birthplace, HPSC and education, a little bit smaller than Table 5 then. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. HPSC is Highest Parental Social Class. See Section 2 for further details.

5.3. Geography and lifetime mobility patterns

The results in Table 4 make clear that the most substantial reduction in the coefficient on birthplace size occurs when we control for current and accumulated city size. Consistent with the agglomeration literature, we know from the estimates reported in Table 3 that current and accumulated city sizes both have a positive effect on wages. That suggests that the reduction

[26] Results available on request show that these findings are robust to the reduction of the sample to all workers, to full-time workers only and to lifetime movers and to using the age of leaving education as an alternative measure for education.

in the coefficient on birthplace size occurs because of a positive correlation between birthplace size and the size of cities where individuals work as adults.

In this sub-section we consider this further by providing evidence on lifetime mobility patterns and on the correlation between birthplace and city size. Low lifetime mobility means that, by construction, current and accumulated city size will tend to be strongly correlated with birthplace size. Thus low mobility provides one mechanism through which birthplace size, via its effect on current and accumulated city size, can affect wages.[27] Indeed, as mentioned in the introduction, in the extreme case of complete immobility, birthplace fully determines place of residence and (given relatively small time series variation in city sizes) it makes little sense to try to distinguish between the effect of birthplace and current and accumulated city size.

Because the BHPS provides information on both current location and place of birth, we can use it to assess the extent of lifetime mobility in Britain. We ignore mobility for non-work related reasons – such as study or retirement – and focus on the share of workers who have only ever worked while living in the same place as they were born. The first row in Table 7 shows the overall figures and then broken down by qualification. As the table shows, over 40% of workers have only ever worked in the place where they were born. The breakdown by qualification shows that these figures are decreasing with education level - consistent with the wider literature on the relationship between education and mobility.[28]

The next 4 rows show the figures broken down by the type of area in which the individual was born.[29] The figures provide evidence that mobility also varies with birthplace size – although the major difference is observed in the larger lifetime mobility away from rural areas. The pattern with respect to qualifications is repeated across area types. The final two rows consider similar figures but now focus on whether someone was born in the same place of birth as their parents (these figures are calculated for a sub-set of the 5,361 individuals for whom we observe both parent and individual birthplace). These figures are higher than for the percentage of individuals who have always worked where they were born. This is partly

[27] This assumes that current and accumulated city size are positively correlated with wages consistent with our findings reported in Table 3 and the findings of the wider agglomeration literature.

[28] For example, Diamond (forthcoming) documents that 67% of US citizens live in their birth state, the figure being only 50% for college graduates.

[29] Areas are classified either as rural or urban with urban further divided in to large cities (employment greater than 260,000), medium cities (employment 130,000-260,000) and small cities (employment smaller than 130,000). See Appendix A1 for further details.

explained by the fact that lifetime mobility is increasing with age (and that people tend to have children when they are younger). But the degree of intergenerational persistence in place of birth is still striking.

Table 7: Lifetime mobility: Share of individuals who have always worked in the same area where they were born, by skills (all workers)

% always worked where born	**Total**	**No quals.**	**GCSE eq.**	**A-level eq.**	**Degree**
Total	43.7	51.8	48.7	45.8	30.5
Born in					
Rural	33.2	40.7	37.9	32.9	21.5
Small city	46.5	52.0	53.5	51.7	29.2
Medium city	45.1	57.1	49.4	48.6	28.9
Large city	48.8	57.2	53.8	50.3	37.2
% born same place as (all individuals):					
Mother born	53.8	63.1	56.2	50.5	49.9
Father born	52.8	56.7	56.7	50.1	48.8

Source: Authors own calculation based on BHPS. Notes: Areas correspond to Local Labour Market Areas – see Appendix B1 for details. Education is classified based on the confrontation of the highest educational and academic qualifications variables. GCSE qualification includes those with O-level and CSE; A-level includes those with HND, HNC or teaching qualifications; Degree includes both 1st and higher degree.

Consistent with this, Table 8 shows that the aggregate lifetime mobility figures hide substantial heterogeneity with respect to age. The table shows overall lifetime mobility at four particular cut-offs – age 16 (compulsory schooling age), age 18 (end of schooling), age 21 (the age at which most university graduates complete their course) and age 65 (retirement).[30] The figures show that nearly 61% of 16 years olds live in the same places as they were born, 55.5% of 18 year olds and 46% of 21 year olds. The full set of figures (available on request) show a gradual decline until age 56, with figures increasing slightly afterwards, suggesting some return migration for retirement.

Table 8: **Lifetime mobility across the UK: Share of (all) individuals who live in the same area where they were born, by skills, by age**

% live in area where born	**Total**	**No quals.**	**GCSE eq.**	**A-level eq.**	**Degree**
At age:					
16	60.8	59.3	60.4	65.3	70.6
18	55.6	59.5	59.1	50.5	62.1
21	46.0	59.3	53.2	41.5	37.1
65	44.4	53.4	40.8	41.6	28.1

Source: Authors own calculation based on BHPS. Notes: See Table 7.

[30] Note that these figures are calculated for all individuals, rather than focusing on mobility for work (which would make no sense for many 16-21 year olds who are still in education and thus outside the labour force).

As discussed above, in addition to being of substantive interest, these figures also help with the interpretation of the regressions including birthplace. In particular, they tell us that for around 60% of our sample birthplace also identifies the area where the individual grew up.[31] For many more, we would expect birthplace to identify the area in which they spent the majority of their childhood (assuming that the gradual increase in mobility with respect to age, as evidenced in Table 8 and in more detailed results available on request, can be extrapolated in to childhood).

Table 9: Regressions of current city log size on birthplace and controls

	(1)	(2)	(3)
Full sample			
(log) Birthplace size	0.375***	0.374***	0.373***
	(0.011)	(0.011)	(0.011)
Observations	109,842	109,842	109,842
R-squared	0.211	0.212	0.220
Movers only			
(log) Birthplace size	0.039***	0.032***	0.032***
	(0.009)	(0.009)	(0.009)
Observations	63,479	63,479	63,479
R-squared	0.009	0.021	0.051
Time FE	X	X	X
Gender, Age, Age2	X	X	X
HPSC		X	X
Education			X

Sample: non-Northern Ireland, non-students, non-retired for whow we observe birthplace, HPSC and education. Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Education is defined using seven educational dummies, while HPSC is Highest Parental Social Class. See Section 2 for further details.

We now turn to the correlation between birthplace and current city size, which helps explain the reduction in the birthplace effect once we include controls for current and accumulated city size. As expected, there is a strong positive relationship between current city size and birthplace size as shown in the first panel of Table 9 – which report estimates from regressions of current city size on birthplace size.[32] Column (1) reports results from the

[31] It is possible that some families move away from birthplace, returning before their children are aged 16 or older. We expect this to affect only a small number of families.

[32] Results available on request show that these findings are robust to considering all workers, to considering full-time workers, only estimating on individuals born 1966 onwards (to allow for the fact that our city size and unemployment data begin in 1971 and that we match individuals to the nearest census year) and with linear interpolation between census year

regression controlling for individual characteristics, while columns (2) and (3) show that controlling for parental characteristics and for own education make no difference – with the coefficient on birthplace size and the R-squared of the regressions remarkably stable across specifications. This finding of a strong correlation between current and birthplace size raises the obvious question of whether the results for birthplace size simply reflect the effect of birthplace inertia – i.e. the fact that mobility is low – so that those born in large places end up working in large places. Remember, however, that results in the column (6) of Table 4 show that this is not the case – the positive effect of birthplace size is similar even when we focus only on lifetime movers. For this sample of lifetime movers, results in Appendix A also show the same pattern in terms of changes to the coefficient on birthplace as we sequentially introduce controls in the two-step regression.

Consistent with this, results reported in the second panel of Table 9 show that for movers the correlation between current city size and birthplace size is still positive, albeit weaker than for the full sample.[33] This helps explain why the reduction of the birthplace effect when adding current city size is weaker for movers than for the full sample.[34] While the strong positive correlation reported in Table 9 for the sample as a whole is driven mostly by inertia (i.e. non-movers), location decision of movers also play a role in helping explain the link from birthplace size to current city size. Including learning effects places a much stronger weight on the full set of adult local labour market decisions and reduces estimates of birthplace effect. The correlation of current and birth city size for movers becomes more important once we allow for accumulated city size. This highlights the difficulties of separately estimating dynamic (i.e. learning) and static agglomeration economies in situations where a relatively large proportion of workers are immobile. See D'Costa and Overman (2014) for further discussion.

5.4 Local unemployment

So far, we have considered how wages are affected by birthplace size. In this subsection we consider whether there is a role for local unemployment in addition to birthplace size. To do this, we include additional controls for birthplace unemployment. Results are reported in

[33] See footnote 32 for robustness checks.

[34] Remember, we can only estimate the specification including accumulated city size for movers. See Section 4 for further discussion.

Table 10.[35] Higher local unemployment at birth has a negative effect on wages. Comparison, to the same columns in Table 4, shows that the coefficient on birthplace is essentially unchanged, consistent with the fact that birthplace size and unemployment are very weakly correlated (the correlation coefficient is -0.099 at the individual level). There are at least three possible explanations for this effect of birthplace unemployment. First, it could be acting as an additional control for parental characteristics, although the fact that the coefficient does not change when introducing HPSC (column 3) suggests that this is perhaps unlikely. Second, it could be capturing a direct effect of growing up in area with high local unemployment – through, e.g., the influences of role models and other mechanisms that have been suggested in the neighbourhood effect literature. Third, it could be capturing the effect of current city unemployment, given the low mobility we have documented and the high time series persistence of local unemployment. Results in column (6) consider this possibility by introducing additional controls for current city unemployment rate. We see that the coefficient on birthplace unemployment is essentially unchanged providing suggestive evidence of a direct effect. Note, however, that once we allow for the possibility of learning – captured once again by accumulated city size – the effects of both birthplace size and unemployment are substantially reduced.[36] Once again, including learning effects places a much stronger weight on the full set of adult local labour market decisions and reduces estimates of birthplace effect.

[35] Results available on request show that these results are robust to considering all workers, the restriction of the sample to workers born 1966 onwards, to adding local unemployment rate at age 16, to adding other local variables at birth and using WLS with inverse of individual fixed effects' variance as weights.

[36] As before, we estimate the specification with accumulated city size for lifetime movers only. See Section 4 for further discussion. As for Table 4, results are essentially unchanged when estimating the specification in column (6) only for movers. With 4,393 observations we get a coefficient on birthplace size of 0.019 (s.e. 0.005) and on birthplace unemployment of -0.022 (s.e. 0.003). The R-squared falls slightly to 0.306.

Table 10: 2nd step regressions of individual fixed effects (gross total wage) on birthplace, unemployment at birth and controls (full time workers only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Birthplace							
(log) Size	0.042***	0.036***	0.035***	0.034***	0.024***	0.023***	0.007
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Unemp.	-0.028***	-0.027***	-0.030***	-0.028***	-0.028***	-0.026***	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
1st-step							
Time FE	X	X	X	X	X	X	X
Occ.				X	X	X	X
City size					X	X	X
Unemp.						X	X
Learning							X
2nd-step							
Gen, Age	X	X	X	X	X	X	X
HPSC		X	X	X	X	X	X
Education			X	X	X	X	X
Obs	7,500	7,500	7,500	7,500	7,500	7,500	3,839
R-squared	0.155	0.207	0.342	0.325	0.322	0.320	0.300

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. City size is current city size; learning is (log) accumulated city size as explained in the text. Age is average age (see footnote 16). Education is defined using seven educational dummies, while occupation uses nine dummies based on one-digit standard occupational classification (SOC). HSPC is Highest Parental Social Class. See Section 2 for further details.

6. Conclusions

This paper considers the link between birthplace size and wages. We show that there is a positive effect of birthplace size on wages and that the magnitude of this effect is similar to that of current city size. A number of mechanisms appear to explain (most of) this effect of birthplace size. First, birthplace size is linked to parental social class so that the sorting of parents explains some of the effect of birthplace size. Once we control for parental social class, there appears to be no additional role for education in explaining the birth size effect. Second, current city size is correlated with birthplace size creating a link from birthplace to current location. As current city size influences wages (as a result of agglomeration economies) the effect of birthplace on current city size is the second mechanism through with the effect operates.[37] Third, because adult learning matters, the effect on current location provides an additional mechanism because it determines the amount of time spent in large cities which increases wages via the effect of adult learning in big cities. Inertia explains some

[37] As an aside, it is interesting to note that the inertia we document here induces correlation in the sorting patterns across generations raising questions about the use of historical instruments that are often used to help identify the causal effect of agglomeration economies.

of these findings: around 40% of workers only ever work while living in the area that they were born. For at least 60% of individuals, place of birth also identifies the area in which a person grows up. But birthplace also plays a role in determining the future location of movers and our results are not fully explained by inertia.

Further work remains to be done on understanding the mechanisms that explain the birthplace size effect and the implications for our understanding of spatial disparities. But, whereas the existing literature has focussed on the role of sorting in adulthood, our results point to the importance of considering other kinds of sorting if we want to fully understand the causes and consequences of spatial disparities.

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Appendix A: Results for movers

As discussed in section 5.3, our main results are robust to restricting the sample to lifetime movers and to an alternative definition of learning defined using accumulated city size whether working or not (footnote 13, p. 11; footnote 19, p.14). Table A1 reports estimates of the birthplace size elasticity for lifetime movers and using the alternative definition of learning (column 7).[38] Results should be compared to those reported in Table 4 of the main text (note that column (7) in Table 4, should be compared to column (6) in Table A1; column (6) in Table 4 showed the result when restricting to lifetime movers – which is reported in column (5) of table A1).

Table A1: 2nd step regressions of individual fixed effects (gross total wage) on birthplace and controls (full time workers only, lifetime movers)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Birth city log size	0.034***	0.026***	0.028***	0.026***	0.024***	0.009*	0.011**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
1st-step controls							
Time FE	X	X	X	X	X	X	X
Occupation				X	X	X	X
(log) City size					X	X	X
Learning						X	X
2nd-step controls							
Gender, Av. age	X	X	X	X	X	X	X
HPSC		X	X	X	X	X	X
Education			X	X	X	X	X
Observations	4,393	4,393	4,393	4,393	4,393	3,839	3,912
R-squared	0.131	0.179	0.315	0.297	0.297	0.300	0.287

Source: Authors own calculation based on BHPS. Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. City size is current city size; learning is (log) accumulated city size as explained in the text. Age is average age (see footnote 16). Education is defined using seven educational dummies, while occupation uses nine dummies based on one-digit standard occupational classification (SOC). HSPC is Highest Parental Social Class. See Section 2 for further details.

[38] Results available on request show that these findings are robust to the reduction of the sample to lifetime movers for whom we observe learning.

Appendix B: Descriptive statistics for cities.

Table B1. Lists of cities and their size (in terms of number of people in employment) by city size category and census years

	Employment					Unemployment rate (%)				
Area	1971	1981	1991	2001	2011	1971	1981	1991	2001	2011
Large cities										
London	4,084,810	3,573,686	3,444,313	4,015,102	4,389,388	3.5	7.5	10.9	6.0	7.4
Manchester	882,333	788,166	747,492	814,821	847,164	4.1	10.1	10.6	5.1	7.2
Birmingham	759,722	677,912	658,353	695,386	696,677	4.0	12.2	11.6	7.4	9.8
Glasgow	600,884	521,019	456,748	450,094	503,452	7.2	13.7	14.4	7.8	9.0
Newcastle & Durham	489,370	458,518	433,490	475,448	483,359	6.1	12.4	12.3	6.9	7.8
Liverpool	493,218	422,646	360,626	388,334	402,108	7.4	16.1	17.1	8.8	9.8
Bristol	342,148	352,524	381,860	447,536	454,164	3.4	7.3	7.9	3.6	5.2
Leeds	382,294	353,946	353,798	402,252	397,465	4.1	9.4	9.2	5.1	7.4
Sheffield & Rotherham	368,003	346,445	328,401	366,811	359,556	3.6	9.9	11.8	6.3	7.8
Leicester	317,828	322,569	337,264	381,127	387,501	2.8	8.0	8.0	4.8	6.5
Nottingham	331,595	321,857	327,558	359,969	358,025	3.7	8.3	9.7	5.6	7.7
Warrington & Wigan	314,163	317,167	321,516	358,610	363,006	3.8	10.1	10.4	5.4	7.1
Guildford & Aldershot	270,224	299,846	329,374	385,903	371,961	2.3	3.9	5.0	2.3	4.0
Luton & Watford	266,697	279,504	294,604	334,886	332,695	2.5	6.1	7.1	3.7	5.9
Cardiff	275,285	264,353	263,504	302,727	320,941	4.8	11.0	11.4	5.5	7.4
Edinburgh	273,489	270,230	267,347	281,312	304,993	4.9	7.5	8.3	4.4	6.2
Medium-size cities										
Southampton	216,737	234,870	260,955	320,639	316,531	3.7	6.2	7.3	3.0	4.8
Portsmouth	223,055	236,063	250,722	294,728	285,171	3.6	7.0	7.9	3.6	5.5
Wycombe & Slough	227,602	240,538	248,622	281,631	278,922	2.5	4.8	6.2	3.2	5.1
Southend & Brentwood	218,765	235,300	247,615	281,366	276,221	3.2	6.7	7.9	4.2	6.1
Maidstone & North Kent	203,618	221,065	244,775	280,510	284,596	4.1	7.3	7.9	4.3	6.2
Coventry	246,992	223,601	225,820	252,537	244,689	3.9	12.0	9.7	5.1	7.4
Reading & Bracknell	184,363	209,266	240,627	284,075	274,658	2.4	4.7	5.5	2.7	4.7
Crawley	188,483	208,533	229,753	279,156	276,567	2.1	4.1	5.6	2.4	4.2
Stoke-on-Trent	241,117	228,873	228,138	240,986	232,462	3.1	8.8	8.0	5.0	6.6
Dudley & Sandwell	231,392	202,563	206,292	219,709	210,275	2.7	11.7	10.9	6.8	9.4
Bradford	213,109	196,874	198,941	213,754	221,256	4.6	11.3	11.0	6.7	9.3
Oxford	167,578	176,453	200,500	244,579	243,534	3.1	6.1	5.8	2.6	4.0

Swindon	151,937	168,298	203,577	247,937	253,641	2.7	6.9	6.1	2.9	4.8
Hull	192,116	187,415	192,671	214,135	216,733	5.1	11.2	11.0	7.1	8.9
Lanarkshire	191,471	196,484	186,888	189,085	216,101	6.4	13.4	12.9	7.3	8.7
Middlesbrough & Stockton	193,488	189,864	183,960	197,146	196,925	5.8	15.2	13.2	8.7	10.3
Rochdale & Oldham	204,937	188,463	179,714	194,889	185,128	3.4	10.7	11.1	5.8	8.9
Swansea Bay	193,180	178,371	168,710	187,672	195,605	4.0	11.8	10.8	6.5	7.0
Northampton & Wellingborough	136,169	152,624	182,247	218,758	221,559	2.5	7.1	6.8	3.9	5.9
Preston	155,418	161,239	174,494	197,488	197,707	3.6	7.8	7.0	3.8	5.1
Norwich	138,886	151,938	172,217	204,900	202,637	3.8	6.6	6.6	4.1	5.2
Wirral & Ellesmere Port	178,064	170,215	165,228	177,006	173,225	4.9	12.0	11.4	6.4	7.7
Brighton	152,568	145,470	158,231	197,315	201,431	3.9	7.2	8.9	4.5	5.3
Cambridge	123,654	140,423	163,401	201,933	214,848	2.5	5.0	5.3	3.0	4.0
Wolverhampton	179,077	161,538	161,748	173,397	166,736	3.7	13.3	12.1	7.1	10.7
Derby	149,490	151,787	159,345	177,617	183,189	3.8	6.9	8.0	4.9	6.5
Milton Keynes & Aylesbury	86,350	123,650	167,676	213,068	226,570	2.1	6.8	6.7	3.4	5.6
Ipswich	130,926	141,231	160,665	190,343	192,889	3.7	5.8	6.2	3.7	5.3
Aberdeen	122,240	144,124	166,598	171,443	199,351	3.7	4.9	4.2	3.8	3.9
Walsall & Cannock	153,450	148,422	155,971	170,102	165,124	3.5	10.8	9.9	5.4	8.3
Stevenage	133,789	144,330	151,637	175,924	178,975	2.3	6.3	7.1	3.1	5.3
Chelmsford & Braintree	114,872	133,812	155,187	186,382	185,960	2.5	4.7	6.2	3.1	4.9
Sunderland	158,293	155,537	145,032	156,960	155,836	6.5	13.8	14.2	7.9	9.2
Plymouth	123,449	133,586	144,712	167,564	164,224	4.0	9.0	9.9	4.5	6.0
Wakefield & Castleford	130,747	136,828	136,209	151,417	152,589	4.0	7.7	9.9	5.5	7.3
Newport & Cwmbran	129,499	127,389	131,857	149,040	150,890	4.6	11.5	9.9	5.5	7.4
Blackburn	140,354	130,162	128,561	139,314	138,470	3.5	9.7	8.8	5.2	7.2
Small cities										
York	103,966	114,696	129,250	157,059	158,805	3.4	5.4	5.5	3.4	4.5
Exeter & Newton Abbot	97,576	105,946	123,999	156,219	153,840	4.2	6.7	6.5	3.6	4.3
Peterborough	86,623	103,824	123,923	152,259	158,558	3.2	7.8	8.1	3.8	5.9
Mansfield	116,008	121,451	118,690	130,338	136,296	3.6	6.8	10.1	6.6	6.9
Bournemouth	99,287	99,262	113,805	150,591	150,030	4.4	8.5	8.7	3.9	5.1
Tunbridge Wells	103,149	108,746	120,170	138,983	139,485	2.6	4.4	5.4	2.6	3.9
Doncaster	115,294	117,017	111,128	127,304	130,918	5.1	10.9	13.1	6.8	8.9
Blackpool	115,137	113,324	117,726	131,376	120,926	4.9	9.1	8.6	5.3	7.5

Bolton	116,505	110,527	109,274	121,746	119,195	3.6	10.3	10.3	5.3	7.7
Clacton and Colchester	87,571	97,577	112,054	141,457	135,489	3.9	7.0	8.2	4.1	6.3
Worcester & Malvern	91,221	95,285	108,801	134,565	128,173	2.8	7.7	6.3	3.4	5.3
Huddersfield	100,217	94,531	100,691	112,968	113,691	2.6	9.1	7.9	4.7	6.7
Cheltenham & Evesham	83,594	90,245	100,784	123,134	120,264	3.3	5.4	6.0	3.3	4.4
Barnsley	97,543	96,636	90,214	100,330	105,686	4.9	9.0	12.9	6.5	8.0
Dundee	98,864	92,604	87,188	81,570	88,692	6.9	12.6	11.9	8.4	8.6
Calderdale	90,729	82,235	85,782	95,134	94,009	3.0	9.2	8.6	5.5	7.3
Telford & Bridgnorth	61,912	70,426	88,870	107,625	105,618	3.7	11.9	8.0	4.4	6.5
Poole	64,419	72,389	85,381	103,352	98,702	3.6	6.4	7.2	3.1	4.4
Grimsby	77,417	81,358	80,748	89,306	87,251	5.1	9.9	11.1	7.7	9.0
Bedford	67,716	74,237	79,091	95,619	94,428	3.0	5.9	6.9	4.0	5.9
Burnley, Nelson & Colne	85,226	78,220	75,764	82,855	77,175	4.1	9.4	8.5	5.2	7.7
Gloucester	63,560	69,465	76,955	91,268	93,544	3.5	6.8	6.7	4.0	5.1
Worthing	60,223	66,020	75,303	96,002	91,181	3.1	5.0	6.1	3.0	4.8
Hastings	50,397	51,113	59,634	75,213	73,025	4.1	7.9	8.9	5.3	7.1
Darlington	44,572	44,006	44,736	49,839	50,767	3.8	9.2	10.0	5.9	7.5
Hartlepool	46,094	42,274	38,720	41,347	42,449	7.4	15.6	14.8	8.9	11.9
Rural areas										
East Lincolnshire	127,467	134,761	146,319	179,445	187,165	4.3	8.2	8.2	4.7	5.8
Harlow	118,144	130,939	139,211	164,905	165,048	2.3	5.3	6.5	3.0	4.7
Crewe	99,632	104,421	114,109	136,927	135,809	3.1	7.6	6.9	4.0	5.5
Chester	93,733	94,863	106,428	123,083	120,697	3.4	11.4	7.3	4.1	5.4
Warwick	81,194	85,374	94,999	114,539	113,870	3.0	6.3	5.6	3.2	4.1
Mid. North East	93,509	92,059	93,409	104,017	101,914	4.6	10.7	9.5	6.1	6.8
Ayr	98,190	94,217	94,844	92,942	99,740	4.5	11.9	11.3	8.1	8.6
W. Cornwall	75,541	75,482	89,128	111,394	113,268	5.0	11.8	10.5	5.7	5.0
Irvine	93,524	92,697	90,416	88,323	93,558	6.4	14.7	13.4	8.9	9.9
E. Anglia Coast	75,958	78,817	90,600	105,762	100,519	6.0	9.3	9.1	6.7	7.9
E. Kent	76,272	80,111	85,421	100,071	97,372	5.7	8.8	9.9	6.2	8.2
Salsbury	68,170	71,682	82,721	108,349	105,552	3.1	5.4	5.2	2.6	3.7
S.W. Wales	73,436	78,243	83,837	96,483	101,252	4.7	8.5	9.3	5.8	5.6
N. Forth	81,885	80,489	86,455	86,364	91,776	5.5	9.7	9.6	7.7	8.4
W. Kent	65,348	70,731	81,449	101,185	104,986	4.2	7.5	8.1	4.2	6.1
Bath	74,034	73,701	81,531	97,716	92,428	2.5	6.3	7.2	3.1	4.4

Chichester	64,296	70,563	80,382	103,487	98,524	3.9	6.4	6.3	3.3	4.9
N. Norfolk	65,942	69,244	81,405	100,380	95,863	4.9	8.8	7.7	4.2	5.6
E. Anglia West	56,413	69,975	82,258	101,400	101,704	3.6	6.3	5.9	3.1	4.3
S. Wales Border	74,271	72,940	77,797	88,614	86,895	4.7	11.1	9.3	5.8	7.5
Dorset Coast	62,523	65,479	76,946	97,707	94,377	4.3	6.6	6.9	3.5	4.4
Mid. Wales	58,871	62,474	73,520	90,882	91,419	3.9	7.5	7.0	4.4	4.8
N. Wales Coast	61,319	62,440	72,510	88,579	85,182	4.8	9.6	8.7	5.8	6.6
Chesterford	69,642	68,379	70,117	78,280	77,663	4.2	8.0	10.1	6.7	6.9
S. Devon	59,300	59,132	68,025	88,823	82,563	6.4	10.2	9.6	5.7	6.0
S. Moray	56,290	65,269	73,470	75,984	86,612	4.9	7.4	6.3	5.0	5.3
Morpeth	65,354	67,990	67,398	76,111	75,962	5.7	8.3	10.5	7.2	8.4
W. Highlands	65,540	65,603	72,550	72,592	75,127	5.8	11.4	9.4	6.7	6.8
E Somerset	55,134	58,522	68,079	84,772	84,879	2.9	6.5	7.3	4.0	4.8
W. Lincolnshire	57,483	59,787	67,195	83,693	82,768	5.2	9.1	9.0	4.9	6.6
Canterbury	57,398	61,419	68,430	82,282	81,174	4.8	7.1	8.0	4.3	5.4
Yeovil	52,895	60,272	68,065	85,148	82,834	2.5	4.9	6.3	3.1	4.0
Burton-on-Trent	57,988	61,012	65,908	79,256	82,706	3.0	6.8	7.3	4.2	5.5
Huntingdon	41,996	53,931	69,489	86,159	86,533	2.7	6.0	5.8	2.8	4.4
E. Cornwall	49,061	53,328	65,471	83,718	84,138	5.0	9.5	9.3	4.9	5.5
S. Cumbria	64,500	66,393	68,357	68,049	67,863	4.4	8.3	8.3	7.0	6.5
Livingston	48,471	58,834	68,093	75,015	83,711	6.3	11.8	9.2	5.3	7.3
Kettering	56,148	52,810	64,918	77,528	81,805	3.3	14.4	8.2	4.3	6.0
Falkirk	60,090	62,975	63,315	66,195	76,113	5.6	10.9	10.4	5.8	7.4
Brecon	65,197	62,303	60,684	68,487	70,402	5.2	10.3	11.4	6.1	7.5
Trowbridge	49,356	55,242	63,823	78,074	80,542	2.4	5.6	6.0	3.2	4.6
Basing	41,461	55,825	69,097	79,011	81,070	2.6	4.7	5.6	2.6	4.5
Mid. Wales Border	56,326	56,464	64,916	76,428	71,518	3.0	8.8	7.4	4.0	5.5
N. Devon	49,781	53,840	63,440	79,000	79,111	3.8	6.9	7.3	4.6	4.4
Hereford	52,189	54,131	61,266	76,572	76,012	3.3	6.9	6.7	4.0	4.8
Wrexham	55,285	55,006	61,747	73,941	74,186	4.7	11.6	8.4	4.9	6.1
Eastbourne	48,663	51,381	60,112	80,356	79,330	3.3	5.6	7.0	3.7	5.3
N.W. Wales	54,428	56,600	62,788	71,392	72,931	7.6	11.9	11.2	7.4	6.6
Scottish Borders	57,154	56,750	63,600	65,269	70,607	3.4	6.6	6.2	4.9	5.9
N. Scotland	48,639	59,037	64,460	64,963	74,789	7.0	8.4	9.0	6.6	5.4
Fens	50,070	50,040	58,456	72,417	76,513	4.3	8.7	7.3	4.0	6.3

Harrogate	47,933	53,647	59,157	74,040	71,444	2.7	5.0	4.3	2.7	3.7
Bridgend	53,641	57,632	59,029	66,661	69,219	4.3	10.4	10.3	5.3	7.1
Carlisle	56,539	56,191	60,797	65,431	67,107	3.1	7.7	6.6	5.1	4.9
Scunthorpe	54,993	52,618	58,370	66,042	68,249	3.8	13.7	9.2	5.4	7.1
N. Solway	54,997	55,727	60,564	58,157	63,650	4.2	8.9	7.9	6.8	6.5
W.N. Yorkshire	46,168	48,872	58,300	70,791	68,151	3.6	6.7	4.9	3.3	4.0
Stafford	50,885	52,422	56,651	63,309	62,514	3.9	6.4	5.5	3.8	4.6
Scarborough	46,207	49,628	57,897	67,387	64,574	6.0	9.0	8.3	6.3	7.4
N. Cumbria	51,273	50,355	55,949	63,012	62,655	3.5	8.7	7.1	5.0	4.8
Shrewsbury	46,367	48,275	54,777	65,302	65,756	3.1	6.3	5.8	3.3	4.6
Dunfermline	46,906	52,063	54,155	56,930	63,551	4.7	8.1	9.1	6.4	7.9
Stirling	49,696	51,485	52,313	54,799	60,731	4.1	9.0	9.3	5.6	7.2
Newbury	38,298	44,286	54,467	65,587	65,409	2.8	4.7	4.7	2.4	4.0
W. Peak District	48,024	48,982	52,758	60,876	57,028	2.4	4.9	5.1	3.3	4.2
Lancashire	47,988	47,600	51,229	59,247	58,849	5.2	9.1	8.0	5.8	5.4
Banbury	35,716	42,707	49,498	63,986	62,313	3.5	5.5	6.5	2.5	3.8
Isle of Wight	41,139	42,879	48,354	61,557	58,051	5.3	9.1	9.7	5.9	7.1
Perth	44,313	43,504	50,003	53,140	60,727	4.1	7.1	5.7	4.3	5.0
Taunton	39,793	40,983	45,524	57,930	58,004	2.5	5.7	6.7	3.5	3.9
Worksop	43,717	44,907	46,582	51,216	53,625	4.4	7.9	9.6	6.5	6.2
N.W. Devon	34,429	36,383	44,922	57,604	60,199	3.5	7.6	7.3	5.0	5.0
E.N. Yorkshire	37,568	37,435	40,626	51,646	51,735	2.7	5.1	4.4	3.1	3.8
Inverness	29,777	35,566	42,356	46,685	58,126	5.6	7.5	7.3	5.8	5.3
E. Highlands	34,837	35,413	40,075	40,279	45,248	4.1	8.4	6.9	5.3	5.7
Rugby	32,473	34,124	36,762	41,838	44,723	3.0	6.5	6.4	4.0	5.2
Kendal	30,517	30,981	36,752	43,484	41,138	2.6	4.6	3.2	2.7	2.7
Andover	26,204	28,851	33,115	41,623	42,856	2.8	4.9	5.3	2.3	3.9

Source: Authors aggregation at the local labour market level of TTWA level data built from the UK censuses by Amior and Manning (2016).

Appendix C: Standard Occupational Classification

Table C.1. List of the job categories represented by the one-digit SOC classification:

Code	Description
1	Managers and Senior Officials
2	Professional Occupations
3	Professional and Technical Occupations
4	Administrative and Secretarial Occupations
5	Skilled Trades Occupations
6	Personal Service Occupations
7	Sales and Customer Service Occupations
8	Process, Plant and Machine Operatives
9	Elementary Occupations