Review of Economic Studies (2013) **80**, 145–173 doi:10.1093/restud/rds019

Advance access publication 18 April 2012

The Effect of Immigration along the Distribution of Wages

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First version received April 2008*; final version accepted December* 2011 (*Eds.*)

This paper analyses the effect immigration has on the wages of native workers. Unlike most previous work, we estimate wage effects along the *distribution* of native wages. We derive a flexible empirical strategy that does not rely on pre-allocating immigrants to particular skill groups. In our empirical analysis, we demonstrate that immigrants downgrade considerably upon arrival. As for the effects on native wages, we find a pattern of effects whereby immigration depresses wages below the 20th percentile of the wage distribution but leads to slight wage increases in the upper part of the wage distribution. This pattern mirrors the evidence on the location of immigrants in the wage distribution. We suggest that possible explanations for the overall slightly positive effect on native wages, besides standard immigration surplus arguments, could involve deviations of immigrant remuneration from contribution to production either because of initial mismatch or immigrant downgrading.

Key words: Immigration, Impact, Wage distribution

JEL Codes: J21, J31, J61

1. INTRODUCTION

This paper analyses the effect of immigration on the wages of native-born workers along the *distribution* of native wages. Our analysis is for the U.K., which experienced an increase of its foreign-born population equal to 3% of the native population over the period between 1997 and 2005.

Our paper adds to the current literature on immigration in various ways. First, we propose a simple estimation method that allows assessing the effect immigration has on native workers at each point in the native wage distribution, without pre-assigning immigrants to particular skill groups. Secondly, we provide a clear theory-based interpretation to the estimated parameter and show that it is proportional to the density of immigrants along the native wage distribution. Finally, we address the overall positive wage effect that we find, and we propose, and assess, alternative explanations for this.

We commence with a general theoretical discussion. First, we note that the common notion that immigration depresses the *average* wages of native workers is based on a simple one-industry model, where capital is fixed.[1]

We develop a model with not just two, but many, skill types and capital as factors of production. We show that, whenever the immigrant skill composition differs from that of the native labour force, and if capital is elastic in supply, the effect on the *average* wages of native workers should be zero or even slightly positive. This result is unsurprising as it is based on a simple surplus argument but has, in our view, not received sufficient attention in the literature on the effects of immigration, where capital supply is usually assumed as being fixed, so that the surplus goes mainly to capital owners.

Although the overall wage effect of immigration may therefore be close to zero, the effects of immigration should be differently felt along the wage distribution, possibly depressing the wages of workers who are in segments of the labour market where the density of immigrants is higher than that of native workers. This calls for an empirical approach that investigates the impact of immigration along the wage distribution. Earlier papers do distinguish between the wage effects on skilled and unskilled workers (see, *e.g.* Altonji and Card, 1991; Card, 2001; Friedberg, 2001; Borjas, 2003; Dustmann, Fabbri and Preston, 2005; Jaeger, 2007) and/or analyse the effect of immigration on *relative* wages (see, *e.g.* Card, 1997, 2005; Card and Lewis, 2007; Glitz, 2011; Manacorda, Manning and Wadsworth, 2012; Ottaviano and Peri, 2012). These approaches require pre-allocation of immigrants to skill groups, based on their observable characteristics.[2] We demonstrate for the case of the U.K. that immigrants downgrade upon arrival and that pre-allocation of immigrants according to their *measured* skills would place them at different locations across the native wage distribution than where we actually find them. This may be problematic when estimation is based on differences between time periods, as only recent arrivals will affect estimates.[3]

We suggest a strategy that circumvents this problem. Based on our theoretical framework, where we allow for many different skill types, we derive an estimable model where we allocate immigrants to skill groups according to their observed position in the native wage distribution rather than pre-allocating them to skill groups according to their observed characteristics. We then estimate the wage effects of immigration across the distribution of native wages. With this approach, no *ex ante* restriction is imposed on where immigrants compete with natives. A key assumption of our method, which identifies skill types with their position in the wage distribution, is rank insensitivity: immigration must not change ranks in the wage distribution. We derive a simple test for this assumption. Based on our data, we find that rank insensitivity holds in our case.

Our empirical investigation first demonstrates that immigrants to the U.K. over the period we consider are on average far better educated than natives. But while perfect substitutability of immigrants with natives within measured age–skill groups would imply that immigrants are located at the upper and middle part of the wage distribution, their *observed* location after arrival is at the lower end of this distribution. Our estimated wage effects along the wage distribution are strikingly in line with the observed location of immigrants: while immigration depresses wages below the 20th percentile, it contributes to wage growth above the 40th percentile.

1. See also Ottaviano and Peri (2012) and Lewis (2011) for a critical assessment of this assumption.

2. Card (2009a,b) defines skill groups according to the quartile of the wage distribution where a worker would be predicted to be located. This is similar in spirit to our approach.

3. See Dustmann and Preston (2012) for an illustration of how downgrading can lead to misleading estimates of the elasticity of substitution between immigrants and natives in approaches suggested by Manacorda, Manning and Wadsworth (2012) and Ottaviano and Peri (2012).

We also find that the *average* effects of immigration on wages are slightly positive. This is in principle possible within a model where capital supply is elastic, due to complementarities of workers at different parts of the wage distribution. Simulations of our model, based on the *actual* distribution of immigrants across the wage distribution, suggest that the *average* wage effects we find, although relatively modest, are too large to be explained by such a surplus argument alone. In the last section of the paper, we discuss possible alternative mechanisms that may explain our estimates, like deviations of immigrant remuneration from contribution to production because of either initial mismatch or immigrant downgrading.

2. THEORETICAL AND EMPIRICAL FRAMEWORK

We commence by setting out a theoretical framework within which to interpret the empirical results that follow. We elaborate a model of labour market equilibrium with workers fully employed, where we allow for only one output and make the assumption that production follows a nested constant elasticity of substitution (CES) technology. We analyse the model under different assumptions about the elasticity of capital supply and develop the empirical implications of the model.

Several of the qualitative conclusions continue to hold in a more general model, which restricts neither the number of industries that may produce different products, the number of labour input types, nor the number of capital inputs into production, as shown in Appendix A.

2.1. *Theory*

2.1.1. The basic model. Following much of the literature on the effect of immigration on wages,[4] we assume that the number of output types (output being denoted y) is equal to one. However, we allow for a multiplicity of labour types, $i = 1, \ldots, L$. Let the output be traded on world markets at a fixed price, which we normalize to equal 1.

We adopt a nested CES production function whereby if labour supplied by the ith type is l_i and capital used is K, then

$$y = [\beta H^s + (1-\beta)K^s]^{1/s},$$
$$H = \left[\sum_i \alpha_i l_i^\sigma\right]^{1/\sigma}, \tag{1}$$

where H is a CES aggregate of purely labour inputs,[5] α_i determines productivity of the ith type of labour, and $\sigma \leq 1$ determines the elasticity of substitution between labour types, while β determines relative productivity of labour and capital and $s \leq 1$ determines the elasticity of substitution between capital and labour. Firms can employ either native labour l_i^0 or immigrant labour l_i^1 of each type i.

We assume that native and immigrant labour of the same type are both perfect substitutes and equally productive: $l_i = l_i^0 + l_i^1$.[6] For the markets for each labour type to clear, $l_i = n_i$ for all i,

4. See, *e.g.* Altonji and Card (1991), Borjas (2003), Card and Lewis (2007), Manacorda, Manning and Wadsworth (2012), and Ottaviano and Peri (2012). We therefore exclude possible alternative adjustments to immigration in a world with traded goods through changing output mix, as discussed by, *e.g.* Lewis (2004) and Dustmann and Glitz (2011). We also exclude adjustment through technology, see Lewis (2011).

5. This formulation is similar to Card (2001).

6. Note that we do not identify labour types with education–age cells; thus, we do not make the assumption criticized by Ottaviano and Peri (2012) and Manacorda, Manning and Wadsworth (2012) that immigrants and natives are perfect substitutes in a given education–age cell.

where n_i is the supply of labour of the ith type. The labour supply is made up of natives n_i^0 and immigrants n_i^1, $n_i = n_i^0 + n_i^1$, so that $n_i = N(\pi_i^0 + \pi_i^1 m)$, where $N = \sum_i n_i^0$ is the total native labour supply, $\pi_i^0 = n_i^0/N$ is the fraction of native labour of the ith type, $\pi_i^1 = n_i^1/\sum_j n_j^1$ is the fraction of immigrant labour of the ith type, and $m = \sum_j n_j^1/N$ is the ratio of the immigrant to native labour force. First-order conditions for profit-maximizing input choice imply that the real wage of the ith type of labour, w_i, equals the marginal product of labour. Similarly, the price of capital, ρ, equals the marginal product of capital. Deriving the first-order conditions and taking logs result in an expression for equilibrium real input prices of all labour types:

$$\begin{aligned}\ln w_i &= \ln \frac{\partial y}{\partial l_i} \\ &= \ln \beta\alpha_i + (\sigma-1)\ln(\pi_i^0 + \pi_i^1 m) + (1-\sigma)\ln\left(\frac{H}{N}\right) \\ &\quad + \left(\frac{1}{s}-1\right)\ln\left[\beta + (1-\beta)\left(\frac{K}{H}\right)^s\right], \end{aligned} \tag{2a}$$

where $\ln\left(\frac{H}{N}\right) = \frac{1}{\sigma}\ln\left(\sum_j \alpha_j(\pi_j^0 + \pi_j^1 m)^\sigma\right)$ and

$$\begin{aligned}\ln\rho &= \ln\frac{\partial y}{\partial K} \\ &= \ln(1-\beta) + (s-1)\ln\left(\frac{K}{H}\right) + \left(\frac{1}{s}-1\right)\ln\left[\beta + (1-\beta)\left(\frac{K}{H}\right)^s\right]. \end{aligned} \tag{2b}$$

2.1.2. The effects of immigration on wages. Let us now turn to deriving the effects that immigration has on wages along the distribution of natives and on the mean wage. Suppose an elasticity of supply of capital given by $\theta = \frac{\partial \ln K}{\partial \ln \rho}$. Then the equilibrium change in native log wages as a reaction to changes in the immigrant–native ratio is shown in Appendix B to be given by

$$\left.\frac{d\ln w_i}{dm}\right|_{m=0} = (\sigma-1)\left(\frac{\pi_i^1}{\pi_i^0} - \phi\sum \omega_j \frac{\pi_j^1}{\pi_j^0}\right), \tag{3}$$

where $\omega_i = \frac{\alpha_i(\pi_i^0)^\sigma}{\sum_j \alpha_j(\pi_j^0)^\sigma}$ is the contribution of the ith type to the labour aggregate H^σ, $\psi = \frac{\beta H^s}{\beta H^s + (1-\beta)K^s}$ is the contribution of labour to the overall CES aggregate y^s, and $\phi = 1 + \left[\frac{(1-s)(1-\psi)}{1+\theta(1-s)\psi}\right]\frac{1}{\sigma-1}$ is a parameter depending on capital mobility θ, capital labour substitutability s, and the labour share ψ. The pattern of the effects of immigration along the native wage distribution therefore depends upon the relative density of immigrants and natives π_i^1/π_i^0 along that distribution.

Consider firstly the case $\phi = 1$, which arises if capital is perfectly mobile ($\theta = \infty$), capital and labour are perfectly substitutable (s =*1*), or the capital share is zero (ψ =1). Since $\sum_i \omega_i = 1$, the rightmost expression in parentheses in equation (3) is the difference at that point in the distribution between the relative density of immigrants and natives and a weighted average of these relative densities across the entire skill distribution. The wage of any skill type is decreased by immigration if, and only if, the intensity of immigration at that point in the distribution of types exceeds an appropriately weighted average of immigration intensity across the whole distribution. If the distribution of skill types in the immigrant inflow exactly matches that in the native labour force, $\pi_i^0 = \pi_i^1$ for all i, then the effect on wages is everywhere zero.

If capital is used, imperfectly mobile and imperfectly substitutable with labour, then $\phi < 1$ and even immigration that matches the native labour force in composition will result in wage losses. However, the pattern of wage effects along the distribution will still be driven in just the same way by the relative density of immigrants and natives π_i^1/π_i^0.

The first-order effect of immigration on mean native wages $\sum_i w_i \pi_i^0$, also derived in Appendix B, is

$$\left.\frac{d\sum w_i \pi_i^0}{dm}\right|_{m=0} = (\sigma-1)(1-\phi)\bar{w}^0 \sum \omega_i \frac{\pi_i^1}{\pi_i^0} \leq 0, \tag{4}$$

where $\bar{w}^0$ is the mean native wage before immigration. The first-order effect is negative unless $\phi = 1$ or $\sigma = 1$. Native labour on average is harmed by immigration, though obviously some labour types may gain if the composition of immigrant and native labour differs.

However, if capital is perfectly mobile so that $\phi = 1$, then the first-order effect is zero. Capital inflows follow the inflow of labour to keep the marginal product of capital constant, immigrant labour is paid the value of its marginal product, and there is no change at the margin in payments to native labour. Turning for this case to second-order effects, we obtain (as shown in Appendix B)

$$\sum \pi_i^0 \left.\frac{d^2 w_i}{dm^2}\right|_{m=0} = (1-\sigma)\bar{w}^0 \left[\sum \omega_i \left(\frac{\pi_i^1}{\pi_i^0}\right)^2 - \left(\sum \omega_i \frac{\pi_i^1}{\pi_i^0}\right)^2\right] \geq 0$$

so that second-order effects on the mean native wage are positive if the immigrant inflow differs at all from native labour in its mix of skill types. Note that the bracketed term is a weighted variance: it is larger the larger the disparity between the immigrant and native skill distribution and disappears only if $\pi_i^0 = \pi_i^1$ for all i. For small levels of immigration, we should therefore expect to find mean native wages rising if capital is perfectly mobile. Indeed, there can be a positive surplus for labour if capital is mobile and immigrant labour sufficiently different to native labour, as we discuss in Section 5.4 and in the Online Appendix where we assess the magnitude of that surplus for our data. This is the conventional "immigration surplus" argument establishing that immigration is beneficial to native factors—immigrating labour is paid less than the value of what it adds to production and the surplus must be returned to native factors if profits are zero.[7]

That does not, of course, mean that in this case wages increase throughout the native skill distribution. Wages fall at any point in the distribution at which π_i^1/π_i^0 exceeds the weighted average $\sum \omega_i \pi_i^1/\pi_i^0$. In particular, it will be those who compete with immigrants who will suffer wage losses.[8]

2.1.3. Rank insensitivity. In our empirical application, we identify skill types with the position in the wage distribution. For this to make sense, it is important for immigration not to change ranks in the wage distribution. A natural justification for this would be to think of individual wages as ordered by a one-dimensional underlying skill level, as in Fortin and Lemieux

7. Appendix A establishes that these qualitative observations apply in a much more general model with many outputs and many perfectly mobile capital inputs, assuming only constant returns to scale.

8. For example, any native subgroup of identical composition to immigrants must lose as shown in Appendix B

$$\left.\frac{d\sum w_i \pi_i^1}{dm}\right|_{m=0} = (\sigma-1)\bar{w}^0 \left[\sum \omega_i \left(\frac{\pi_i^1}{\pi_i^0}\right)^2 - \phi\left(\sum \omega_i \frac{\pi_i^1}{\pi_i^0}\right)^2\right] \leq 0.$$

(1998). In the CES setting, it would be natural to associate this skill level with the productivity parameter α_i. However, equation (2a) does not guarantee that the ordering by α_i coincides with the ordering by wages before immigration unless $\ln(\alpha_i/\alpha_j) > (1-\sigma)\ln(\pi_i^0/\pi_j^0)$ whenever $\alpha_i > \alpha_j$. This condition could hold naturally given the distribution across skill types. But even if it did not, because, *e.g.* low-skilled types were in such short supply relative to high-skill types that low-skilled jobs commanded a premium, it would come to hold if high-skill types were to respond by moving costlessly down to lower skill jobs in search of higher wages.

However, we do not need to assume wages ranked by an underlying skill index in this way to ensure that positions in the wage distribution should be unaffected by immigration. What is needed for rank insensitivity is that immigration does not disturb too dramatically the distribution of labour across skill types, and this is, in fact, testable.

To be precise, let w_i^0 denote the wage before immigration, which is to say the wage at $m = 0$. Then, from equation (2a), noting that $\ln(1+x) \approx x$ for small x,

$$\begin{aligned}\ln(w_i/w_j) &= \ln(w_i^0/w_j^0) - (1-\sigma)\ln\left(\frac{1+(\pi_i^1/\pi_i^0)m}{1+(\pi_j^1/\pi_j^0)m}\right)\\ &\approx \ln(w_i^0/w_j^0) - (1-\sigma)m\left(\frac{\pi_i^1}{\pi_i^0} - \frac{\pi_j^1}{\pi_j^0}\right).\end{aligned}$$

Immigration preserves the ranks of individuals if and only if

$$m\left(\frac{\pi_i^1}{\pi_i^0} - \frac{\pi_j^1}{\pi_j^0}\right) \approx \ln\left(\frac{1+(\pi_i^1/\pi_i^0)m}{1+(\pi_j^1/\pi_j^0)m}\right) \geq \frac{1}{1-\sigma}\ln(w_i/w_j) \tag{5}$$

whenever $w_i > w_j$. Clearly, if π_i^1/π_i^0 is increasing along the post-immigration wage ranking, this will have put more downward pressure on wages higher up the post-immigration wage distribution, so that the pre-immigration ranking cannot have been different. This is not necessary, however—even without increasing π_i^1/π_i^0, rank insensitivity may hold, as long as π_i^1/π_i^0 does not decrease too fast. Condition (5) describes exactly the necessary and sufficient condition, which extends this intuition, and which can be checked, given a value for σ. For plausible values for σ and for values of m such as seen in our data, the condition could fail only given extraordinarily strong concentrations of immigrants within narrow ranges of the wage distribution. For our application, we show below (Section 5.1) that rank insensitivity holds.

2.2. *Empirical specification*

We now turn to empirical implementation motivated by the CES model as outlined above. Take the factor return equations (2a)–(2b), combine with a capital supply equation, and let ρ_0 be the equilibrium return to capital at $m = 0$.

Taking a first-order Taylor expansion of equation (2a) around $m = 0$ using the earlier expression $\frac{d\ln w_i}{dm}\big|_{m=0} = (\sigma-1)\left(\frac{\pi_i^1}{\pi_i^0} - \phi\sum\omega_j\frac{\pi_j^1}{\pi_j^0}\right)$, we obtain an approximate expression for the wage of the ith type:

$$\ln w_i \approx \ln\beta\alpha_i + (\sigma-1)\ln\pi_i^0 + \tfrac{1-\sigma}{\sigma}\ln\left(\sum_j \alpha_j(\pi_j^0)^\sigma\right) + G(\rho_0) + (\sigma-1)\zeta_i m, \tag{6}$$

where $G(\rho) = \ln\left(\frac{\rho}{1-\beta}\right) + \frac{s-1}{s}\ln\left[\frac{1}{\beta}\left(\frac{\rho}{1-\beta}\right)^{s/(1-s)} - \frac{1-\beta}{\beta}\right]$ and $\zeta_i = \left(\frac{\pi_i^1}{\pi_i^0} - \phi\sum\omega_j\frac{\pi_j^1}{\pi_j^0}\right)$.

Our data come from different regions at different points in time and our empirical approach is based on using variation in immigrant inflows across different regions in the U.K. For each region and each period, we have a sample covering native and immigrant workers, large enough to allow us to estimate immigrant numbers and large enough for natives to allow us to estimate the distribution of native wages. We choose to identify different skill types i with different locations in the observed distribution of native wages.[9] In other words, if W_{prt} denotes the pth percentile of the native wage distribution in region r at time t, then, in terms of the earlier theory, we identify this with w_i where i is the smallest value such that $\sum_{j\leq i}\pi_j^0 \geq 100p$.

Accordingly, we adopt a model

$$\ln W_{prt} = a_{pr} + b_{pt} + c_p X_{rt} + (\sigma - 1)\zeta_{prt} m_{rt} + \varepsilon_{prt}, \tag{7}$$

where at each point in the distribution p we include region and time effects, $a_{pr} + b_{pt}$. The former capture the role of technological parameters given the initial skill distribution and capital price in the region, whereas the latter capture the influence of changes in national capital prices on the chosen capital–labour ratio.[10] Controls for changing age and skill composition of the native labour force are included in X_{rt}. Finally, ε_{prt} is a random error term.

The key term of interest is that capturing the impact of immigration $(\sigma - 1)\zeta_{prt} m_{rt}$. If we assume constancy across regions and time ($\zeta_{prt} = \zeta_p$), then regression of log wages along the native wage distribution on immigration intensity m_{rt} picks up a constant parameter $\gamma_{prt} = (\sigma - 1)\zeta_p \equiv \gamma_p$ at each point in the distribution. This parameter is the percentage change in wages at that particular part of the wage distribution if the immigrant–native ratio changes by one percentage point. This parameter has a clear interpretation: it should inversely vary with the density of immigrants along the native wage distribution. We will estimate this parameter for five-percentile steps of the native wage distribution. Our estimates should be inversely related to estimates of the density of immigrants along the native wage distribution (see equation (6))—which we can obtain from independent information in our data. We show below that these two pieces of information have exactly the expected correspondence. If the ζ_{prt} were not constant across time or regions, the estimated parameter $\hat{\zeta}_p$ would be an average across region and time provided ζ_{prt} were not correlated with m_{rt}.

To check the constancy of the ζ_{prt}, we could estimate these from our data. This would also in principle allow us to estimate the underlying structural parameters σ and ϕ. However, although our data give us accurate measures of the region-specific immigrant–native ratio m_{rt}, we do not have enough sampled immigrants in each region at each point in time to measure ζ_{prt} or its components accurately for each percentile p of interest. Nevertheless, to check the constancy of the relative density of immigrants along the native wage distribution across time and regions, we can pool across regions and time periods to provide some information on where immigrants are located in the native wage distribution. If the assumption that ζ_{prt} is constant across r and t is accurate, then the pattern of how γ_p varies across the distribution should

9. Since the number of natives falling within any percentile range of the native wage distribution is intrinsically unvarying, this means that the native skill proportions π_i^0 do not vary. Insofar as there is an assumption involved here, it relates to the correspondence between skill types and positions in the native wage distribution. If this is not constant, then it would show up not as non-constancy of the native skill proportions but rather as non-constancy in the correspondence between skill parameters $\alpha_{i,t}$ (which now need to carry time subscripts) and positions in the native wage distribution. Without a definition of skill types in terms of observable characteristics divorced from position in the wage distribution, which we are unable to pursue because of a lack of suitable measures in the data and the problems with downgrading of immigrant skills noted in the paper, it is not possible to explore this further.

10. It seems reasonable to assume that capital is perfectly mobile between regions (but not necessarily internationally). In that case, the capital price would be the same in all regions and any influence of immigration on the national capital price would be absorbed fully in the time effects. In such a case, it would make sense to identify $a_{pr} = (\sigma - 1)\ln(\pi_i^0) + \frac{1-\sigma}{\sigma}\ln\left(\sum \alpha_j (\pi_j^0)^\sigma\right)$ and $b_{pt} = \ln \beta\alpha_i + G(\rho_0)$.

mirror the way that estimates of ζ_p, say $\hat{\zeta}_p$, vary across the distribution—which is what we find. This provides a simple visual check on the correspondence of the theoretical framework we are adopting to interpret results with the actual pattern of wage changes in response to immigration.

We can go further by pooling across regions or time periods to give us some idea of how ζ_{prt} varies across r and t. We show in the descriptive part of the paper that the ζ_{prt} are very similar across regions and over time.

A further, more visual way to obtain an estimate of $(\sigma-1)$ is to plot estimates of $\hat{\gamma}_p$ against $\hat{\zeta}_p$, assuming perfectly elastic supply of capital ($\phi=1$). We show in Section 5 that this gives similar estimates of $(\sigma-1)$ along the percentiles of the distribution and of a plausible magnitude.[11]

3. BACKGROUND, DATA, AND DESCRIPTIVES

3.1. *The data*

The main data set we use for our analysis is the U.K. Labour Force Survey (LFS) over the period from 1997 till 2005. The LFS, established in 1973, is a sample survey of households living at private addresses. We restrict our analysis to Great Britain. Since 1992, the LFS has been a rotating quarterly panel. Each sampled address is interviewed five consecutive times at three monthly intervals. The sample size is about 55,000 responding households in Great Britain every quarter, representing about 0·2% of the population.

The LFS collects information on respondents' personal circumstances and their labour market status during a reference period of 1–4 weeks immediately prior to the interview. From the 1997 spring quarter onwards, questions on both gross weekly wages and hours worked were asked during the first and the fifth interview.

Spatial information is available at regional level, where region is determined according to usual residence. The LFS originally identifies 20 regions.[12] We unify Inner and Outer London into Greater London, and Strathclyde and the Rest of Scotland into Scotland, to create territorially homogeneous regions. We have therefore 17 regions, and the usual average sample size for the period we consider is about 19,000.[13]

We combine information from the LFS with information from various years of the U.K. Population Census. The Census is a decennial survey of all people and households. The most recent Census was in 2001. Although providing information on age, education, and employment status, the U.K. Census has no information on wages. Moreover, comparability across Census years is not always possible as variable classifications change quite often. This is for instance the case for occupation and education between the 1991 and 2001 Census. In our analysis below, we use information from the 1991 and 1981 Census to construct variables for immigrants' geographical distribution.

11. Provided that we obtain precise enough estimates of ζ_p, we could also regress log wages on the product $\hat{\zeta}_p m_{rt}$, either percentile-by-percentile to provide point-by-point estimates of $(\sigma-1)$ (which should be roughly constant) or pooling across percentiles to estimate a common $(\sigma-1)$. The problem in this is that the estimation error on $\hat{\zeta}_p$ would not be constant across the distribution but rather systematically related to the position in the wage distribution in a way difficult to correct for.

12. Tyne and Wear, Rest of Northern Region, South Yorkshire, West Yorkshire, Rest of Yorkshire and Humberside, East Midlands, East Anglia, Inner London, Outer London, Rest of South East, South West, West Midlands (Metropolitan counties), Rest of West Midlands, Greater Manchester, Merseyside, Rest of North West, Wales, Strathclyde, Rest of Scotland, Northern Ireland.

13. The average population size in a region is 2,163,121.

TABLE 1
Average age, gender ratio, and education in 1997 and 2005

	Natives		Foreign born			
			Earlier		Recent	
	1997	2005	1997	2005	1997	2005
Age	39·64	41·01	40·67	40·49	29·09	29·54
% Female	51·30	51·93	54·27	54·23	56·76	50·86
Education						
% High	11·64	16·02	25·49	33·81	49·25	45·40
% Intermediate	23·38	26·41	33·31	34·22	39·62	40·73
% Low	64·98	57·57	41·20	31·97	11·13	13·87

Notes: Entries are the average age, the percentage of female, and the share of working-age (16–65) natives and immigrants of both sexes in each education group in 1997 and 2005. High education: left full-time education at age 21 or later. Intermediate education: left full-time education between age 17 and 20 (included). Low education: left full-time education not after age 16 or never had full-time education. *Source:* LFS 1997, 2005.

3.2. *Migration to the U.K. and descriptive evidence*

In 1971, the percentage of foreign-born individuals in the total population in Great Britain was 5·9%, or 3 million individuals. Over the next decades, this number increased to 6·3% (1981), 6·8% (1991), and 8·5% (2001). The share of foreign-born individuals in the total working age population in 2005 was 11·5%, smaller than the corresponding share in the U.S., which was 14·9% in the same year.[14] While between 1989 and 1997, the foreign-born working-age (16–65) population on the total working-age population increased by only 0·7 percentage points, it increased by almost 3 percentage points between 1997 and 2005. This is the period we consider for our analysis, and we concentrate on the working-age population only.

Table 1 reports some characteristics of the native-born and foreign-born population in Britain, where among the foreign-born we distinguish between earlier and more recent immigrants. We define as "earlier immigrants" all foreign-born individuals who have been in the U.K. 2 years or more at the time of interview; we define as "recent immigrants" all immigrants who arrived in the U.K. over the last 2 years. This distinction is important as our empirical analysis is based on variation in the stock of immigrants between two subsequent years; this variation is driven by recent arrivals.

In Table 1, we report average age and educational attainments for 1997 and 2005, the first and the last year of our observation period. Natives and earlier immigrants are very similar in their average age (around 40), while new immigrants are about 10 years younger. The percentage of females on the other hand is roughly similar, with a slight drop for more recent immigrants between 1997 and 2005.

The lower panel of the table reports educational attainment of the different groups. We base our measures on information about the age at which the individual left full-time education,[15] and we classify individuals in three groups: low (left full-time education before the age of 17), in-

14. Sources: U.K. LFS for the U.K. and U.S. Census Bureau, Current Population Survey, Annual Social and Economic Supplement, 2005

15. The LFS has two alternative measures for educational achievements, age at which individuals left full-time education and "highest qualification achieved". The problem with the latter measure is that it is defined on the British education system and classifies all foreign classifications as "other qualification" (see the discussion in the appendix of Manacorda, Manning and Wadsworth, 2012).

TABLE 2
Occupational distribution in 2004 and 2005

	Natives	Foreign born		Average
		Earlier	Recent	wage
Higher managerial and professional	14·95	21·70	16·33	18·92
Lower managerial and professional	31·49	31·40	20·26	12·99
Intermediate occupations	13·99	11·18	8·76	8·60
Lower supervisory and technical	12·36	9·31	6·63	8·51
Semi-routine occupations	16·02	15·81	22·33	6·62
Routine occupations	11·19	10·61	25·69	6·74

Notes: Entries are the share of working-age (16–65) natives and immigrants of both sexes in each occupation group in years 2004–2005 pooled. Average wage is the (weighted) average wage in the occupation in 2004–2005, expressed in 2005 terms. *Source:* LFS 2004, 2005.

termediate (left full-time education between 17 and 20 years), and high (left full-time education after age 20). For natives and earlier immigrants, the table shows an improvement in educational attainment between 1997 and 2005. However, earlier immigrants are better educated than natives in both years, with a higher percentage in the highest category and lower percentages in the lowest category. Nearly one in two of new arrivals is in the highest educational category and slightly more than 1 in 10 in the lowest category. The educational attainment of new arrivals has roughly remained constant over the period considered.

3.3. *Downgrading and the density of immigrants along the native wage distribution*

Recent immigrants may not be able to make use of their educational background to its full potential as they may lack complementary skills like language or they may have to start searching for their best job match (see Eckstein and Weiss, 2004). In Table 2, we display the occupational distribution of immigrants in 2004 and 2005, where we distinguish between six occupational categories using the National Statistics Socio-economic Classification (NS-SEC). We exclude employers and the self-employed because we do not have information on their wages. The last column shows the average wage by occupation in the years considered, expressed in 2005 prices.[16]

The occupational distribution of those who have been in the country for at least 2 years is similar to the native-born, except for the higher immigrant concentration in the highest paid category and the slightly higher concentration of natives in the two intermediate categories. However, recent immigrants, *i.e.* those who arrived within 2 years of the interview, although being better educated than the overall immigrant population (see Table 1), tend to be in lower occupation categories, with the partial exception of higher managerial and professional occupations: 48% are in the lowest two occupational groups, compared with 27% of natives and 26% of earlier immigrants. This suggests that new arrivals, unable to put their human capital into immediate use, start lower down the occupational distribution and compete with native workers much further down the distribution. This finding mirrors results for Israel on the considerable downgrading of new immigrants—see the work by Eckstein and Weiss (2004).

In Table 3, we break down the occupational distribution by educational attainment, using the same grouping. The figures show that within each education group, recent immigrants are distributed more towards the lower end of the occupational distribution. For instance, while

16. We discount wages using the 2005-based Consumer Prices Index.

TABLE 3
Occupation by level of education in 2004 and 2005

	High education			Intermediate education			Low education		
		Foreign born			Foreign born			Foreign born	
	Natives	Earlier	Recent	Natives	Earlier	Recent	Natives	Earlier	Recent
Higher managerial and professional	36·86	39·66	28·96	15·42	12·85	4·48	7·06	5·84	3·63
Lower managerial and professional	47·29	36·42	29·15	37·8	33·87	13·59	22·74	19·99	6·34
Intermediate occupations	8·22	8·68	9·51	18·5	14·71	9·81	13·66	10·10	1·81
Lower supervisory and technical	2·68	4·28	5·16	9·08	9·71	8·34	17·52	16·76	8·46
Semi-routine occupations	3·78	7·44	14·98	13·3	18·38	29·34	21·59	25·47	29·61
Routine occupations	1·16	3·53	12·24	5·9	10·49	34·44	17·43	21·84	50·15

Notes: Entries are the share of working-age (16–65) natives and immigrants of both sexes in each occupation group by level of education in 2004–2005 pooled. *Source:* LFS 2004, 2005.

among highly skilled natives, only 5% work in the lowest two occupational categories, this is the case for 11% of earlier immigrants, but 27% of recent immigrants. The respective numbers for the intermediate education category are 19%, 29%, and 64%. Again, this suggests considerable downgrading of recent immigrants within educational categories.

In our empirical analysis, we will associate the changes in wages across different spatial units with the changes in the stock of immigrants. Our theoretical model above suggests that the immigrant population will exert pressure on the wages of natives at those parts of the distribution where the relative density of immigrants is higher than that of the weighted relative density of natives.

Where we actually find immigrants in the native wage distribution can be straightforwardly estimated from the data: in each year, and for each immigrant, we can calculate the proportion of natives with a lower wage.

In Figure 1, the dotted line shows the density of recent immigrants along the wage distribution of natives.[17] Contrary to what we should expect based on information on their educational background, the density of recent immigrants is higher than that of natives everywhere below the 25th percentile of the wage distribution. On the other hand, it is lower between the 25th percentile and the 90th percentile and higher again afterwards. Based on these figures, we should expect therefore that immigrants put pressure on wages below the 25th percentile of the native wage distribution.

Where would we find immigrants along the native wage distribution if we had allocated them according to their observed age and education distribution? We illustrate that with the dashed line in Figure 1. The dashed line is obtained by estimating a flexible log wage regression for natives.[18] We estimate that equation separately for males and females. We predict wages for all recent immigrants, where we add an error term to the prediction, which is drawn from a normal distribution, with heteroscedastic variance according to age, education, and gender. We

17. These are kernel density estimates. Given that the variable in question is bounded, by construction, between 0 and 1, conventional kernel estimation with fixed window width would give misleading estimates at the extremes. The kernel estimates are therefore calculated on the log of the odds of the position in the non-immigrant distribution and appropriately transformed.

18. Our regressors include five age categories (16/25, 26/35, 36/45, 46/55, 56/65), four educational categories, based on age at which individuals left full-time education (before 16, 16/18, 19/20, after 20), interaction between the two, a dummy for London residents, and quarter dummies. We fit separate models for men and women and for different years.

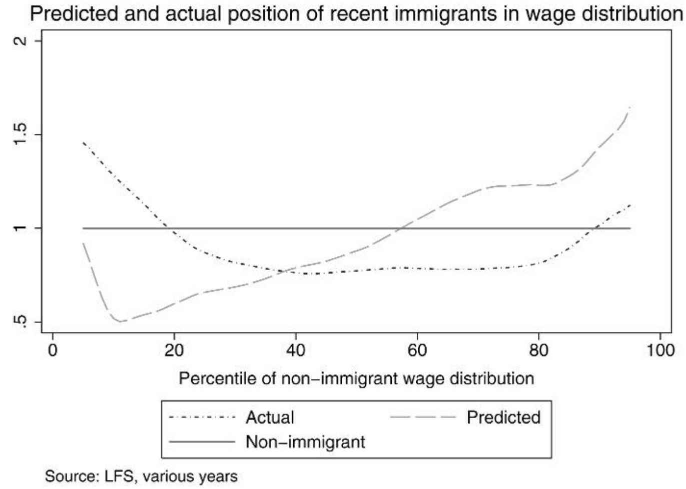

FIGURE 1

The figure shows kernel estimates of the density (dotted line) and the predicted density (dashed line) of immigrants who arrived within the last 2 years in the non-immigrant wage distribution. The horizontal line shows as a reference the non-immigrant wage distribution. The kernel estimates are above the horizontal line at wages where immigrants are more concentrated than natives and below the horizontal line at wages where immigrants are less concentrated than natives

then draw the density of immigrants across the native wage distribution. The difference between the predicted and the actual distribution is striking. In particular, immigrants are predicted to be less concentrated below the 60th percentile and more concentrated above. Based on the predicted distribution, we would expect immigrants to exert a pressure on wages mainly above the median.

These figures and the comparison between Tables 1 and 2 suggest that immigrants are "downgrading" in the sense that they work in different occupations than natives even if they are in the same age–education group.[19] To explore this point further, we have estimated a simple log wage equation for (recent) immigrants and natives, controlling in a flexible way for age, education, and year effects. This regression indicates a log wage gap between immigrants and natives of 0·179. We have then augmented this regression equation with occupation (16) and industry (17) dummies and their interaction. Conditioning on these variables reduces the log wage gap between immigrants and natives by more than 70%, from 0·179 to 0·052, suggesting that the major part of wage differences is indeed explained by occupation/industry allocation and not by differential treatment within occupation/industry. We have also computed a Duncan index of dissimilarity for the distribution of recent immigrants and natives across occupations (classified according to the NS-SEC operational categories) for each of the 21 age–education cells and—alternatively—for 21 cells based on positions in the wage distribution. The effective Duncan index for occupational dissimilarity, averaged across age–education cells, is 34·9—suggesting that about 35% of immigrants would need to change their occupation to achieve the same occupational distribution as natives. The same index is 16·4 across 21 wage cells. This motivates our approach of distinguishing "effective" skill groups by percentiles of the wage distribution, distinguishing groups of immigrants and natives who compete with each other according to where they are situated in the wage distribution.

19. See also Peri and Sparber (2009), who provide evidence that native- and foreign-born workers specialize in occupations with different skill content.

4. ESTIMATION

4.1. *Implementation and identification*

In our empirical analysis, we estimate the effects of immigration along the distribution of wages. Our starting point is the empirical model that derives directly from our theoretical framework, as in equation (7). The parameter we estimate in that model is a combination of the elasticity of substitution between skill groups and the relative density of immigrants at the particular part of the native wage distribution. As we explain above, the relative size of the parameter should directly correspond to the density of immigrants, as illustrated in Figure 1.

The way we implement that model is to regress differences over time in percentiles of log wages across different regions in the U.K. on changes in the fraction of immigrants to natives Δm_{rt}, time dummies β_t, and changes in the average age of immigrant and native workers in the region as well as the ratio of high- (or intermediate-) to low-educated native workers, ΔX_{prt}:

$$\Delta \ln W_{prt} = \beta_t + \Delta X_{prt} + \gamma_p \Delta m_{rt} + \Delta \varepsilon_{prt}. \tag{8}$$

As we point out above, our approach does not depend in any way on pre-assignment of immigrants to particular skill cells. For estimation, we use variation across spatial units r and across time. This approach may potentially lead to an overly optimistic picture of the effect of immigration on native outcomes if natives leave labour markets that experienced in-migration. However, if this occurs, it is likely to be less relevant in our case as the large regional definitions we use in our analysis make it more likely that any movements will be internalized (see Borjas, Freeman and Katz, 1997, for a similar argument).[20] In addition, we condition on native skill group proportions, which should take account of changes in the native skill group over time.[21] Of course, there are concerns about whether such proportions ought themselves to be regarded as endogenous in such a setting and there are less obvious instruments to deal with the issue. Inclusion of these variables has no impact on our estimates.

A further problem is the endogenous allocation of immigrants into particular regional labour markets. One solution is to use instrumental variables estimation. We follow the literature and use settlement patterns of previous immigrants as instruments. This instrument has been used in various studies in this literature, following Altonji and Card (1991), and is motivated by a number of studies (see, for instance, Bartel, 1989; Munshi, 2003) showing that settlement patterns of previous immigrants are a main determinant of immigrants' location choices.[22] Concentration of new immigrants near where previous immigrants are already located is a readily intelligible response to immigrant social and economic networks. When estimating equation (8), we use years 1997–2005, and we compute the ratio of immigrants to natives for each year in each of the 17 regions. Estimation in differences eliminates region-specific permanent effects that are correlated with immigrant settlement patterns and economic conditions alike. We instrument the *change* in this ratio using two alternative but closely related instruments: the 1991 ratio of immigrants to natives for each of these regions, from the Census of Population, interacted with year dummies, and four period lags of the ratio of immigrants to natives in each region from the LFS. Both instrumental variables are strongly correlated to the ratio of immigrants to natives.

20. We nevertheless check this by using an extension of the methodology in Card (2001), adapted to our quantile approach, and find no evidence for native responses to immigration (details are available on request).

21. Note that we implicitly condition on the terms a_{pr} and b_{pt} through differencing and the inclusion of time dummies, which—as we explain in footnote 10—absorbs region-specific densities of natives at any percentile p of the distribution.

22. See among others Card (2001), Card and Lewis (2007), Cortes (2008), Cortes and Tessada (2011), Lewis (2011), and Saiz (2007) for a similar strategy.

The first-stage regression of the change in the immigrant–native ratio on the interacted 1991 ratio and all the exogenous control variables gives an F-statistic for the significance of excluded instruments of 115·53,[23] while the partial R^2 is 0·46. The regression of the endogenous variable on the fourth lag of the immigrant–native ratio and on the other control variables and time dummies gives an F-statistic 163·71, and the partial R^2 of excluded instruments is 0·33. The instruments are valid under the assumption that economic shocks are not too persistent. We report in Table A1 in Appendix C the results of Arellano–Bond tests for first- and second-order serial correlation in the residuals of regressions for all the dependent variables we consider. Absence of second-order serial correlation cannot be rejected for most variables.

In addition, we perform several robustness checks, using instruments that are based on settlement patterns further aback. We use further lags of the ratio of immigrants to natives (going back to the 14th lag) and the 1981 immigrant–native ratio. We also construct a series of instruments based on the predicted inflow of immigrants in each region, along the lines of Card (2001). We take account of the area of origin of immigrants and design a variable which predicts the total immigrant inflow in each region in every year, net of contemporary demand shocks. In order to do so, we divide immigrants into 15 areas of origin[24] and calculate the number of immigrants from each area who entered the U.K. every year. We then allocate every group of immigrants across regions according to the location of previous immigrants from the same area.[25] Results obtained with these alternative instrumental variables are very similar to those obtained with the instruments described above, which we report in the tables (see Table A2 for estimation results for average wages. Results along the distribution are available on request).

4.2. *Measurement*

As we explain in Section 3.2, the LFS is a nationally representative survey, and since the immigrant population accounted for less than 10% of the total population for most of the years we consider (and much less so in some regions), the number of observations for immigrants may be quite small. Therefore, measures of regional immigrant concentration may suffer from measurement error due to small sample size. As we estimate our equations in first differences, this may amplify the impact of measurement error, resulting in a possibly severe downward bias. Instrumental variable estimation accounts for the measurement error problem as long as the measurement error in the instrumental variable is uncorrelated with the measurement error in the variable of interest.[26]

We use four different measures for average wages to test the robustness of our results. First we use the simple average regional wage. Second, we compute a robust regional average by

23. Standard errors are clustered by region.

24. Irish Republic, Old Commonwealth, Eastern Africa (New Commonwealth, NC), Other Africa (NC), Caribbean (NC), Bangladesh, India, Pakistan, South East Asia (NC), Cyprus, Other NC, European Community (1992 members), Other Europe, China, Rest of the World.

25. If we define M_{ct} as the number of new immigrants from area c in year t and $\lambda_{ci} = M_{ci}/M_c$ as the fraction of immigrants from area c in region i in a base period, then $\lambda_{ci} M_{ct}$ is the predicted number of new immigrants from area c in region i in year t. As base periods, we experiment with different years: 1981, 1985, and 1991, using data from the LFS. We then sum over all origin groups to obtain a predicted total immigrant inflow into region i which is "cleansed" of local demand shocks: $\sum_c \lambda_{ci} M_{ct}$. Finally, we divide this predicted inflow by the number of natives in the region at time $t-2$, to normalize by region size.

26. Aydemir and Borjas (2011) argue that, if the instrument of choice is some lagged measure of the immigrant share and measurement error is correlated over time, the instruments may not be valid. In our case, this is not a concern because we use a minimum of four lags as instrument, therefore avoiding any correlation in the measurement error of the endogenous variable and the instrument even in first differences. Alternatively, we use as an instrument the immigrant concentration from the Census, whose measurement error is independent from that in the LFS.

trimming in every region and year the wage distribution of natives at the region- and year-specific 1st and 99th percentile. This measure reduces the impact of outliers on our averages by considering only central observations in the wage distribution. Third, we calculate a wage index constructed as the weighted sum of the average wages in each education group, defined as above in terms of years of education (see discussion in Section 3.3). The educational composition of the native population is kept constant by choosing as weights the share of each education group in the native population in a base year (which we choose to be 1998).[27] By holding constant the skill composition of the assessed population, this measure is isolated from compositional issues associated with changing native skills. The theoretical results of earlier sections show that wage changes could raise average wages in the native population (if capital is perfectly elastic) holding skill composition fixed and this measure comes closest to capturing that. Finally, we use a robust version of this index based on wages in the trimmed sample. The robust index is constructed using robust average wages for each education group, where the average wages by education group are computed on the same trimmed sample as explained above.

The LFS contains sample weights. These are appropriate to the whole population of immigrants and natives rather than simply to natives or immigrants only. We prefer therefore not to use them for the calculation of separate statistics for immigrants and natives.

In Table A3 in Appendix C, we report means and standard deviations of all the variables we use, and in Table A4, we show the year-specific means and standard deviations of the change in the immigrant–native ratio.

5. RESULTS

5.1. *Rank invariance*

An important assumption of our approach is that immigration does not change ranks in the wage distribution. Before we present our main results, we test for rank insensitivity. In equation (5), we report the necessary and sufficient condition for immigration not to affect the ranking of native by wages. Rearranging that expression gives us a condition for no re-ranking to occur:

$$\frac{\left(\frac{\pi_i^1}{\pi_i^0}-\frac{\pi_j^1}{\pi_j^0}\right)}{\ln(w_i/w_j)} \geq -\frac{1}{(1-\sigma)m} \quad \text{whenever } w_i > w_j.$$

In Figure A1 in Appendix C, we plot the left-hand ratio for adjacent percentiles of the native wage distribution. It is apparent from the figure that this ratio never exceeds -2. For an immigration inflow of about 3% of the native population, which we see over the period of our data, this condition cannot fail for values of the elasticity of substitution $(1/(1-\sigma))$ greater than or equal to 0·06, or equivalently, for σ greater than or equal to about -16. Below we estimate the elasticity of substitution to be around 0·6, which is well above this critical value.[28]

27. The wage index is constructed for each region as follows. First we calculate $\overline{w}_{et}$, the average wage for education group $e = 1,2,3$ in time $t = 1997,\ldots,2005$. Then we calculate the time-invariant weights $\pi_{e1998} = N_{e98}/N_{98}$, the proportion of natives in education group e in 1998. Finally, we define the index $I_t = \sum_{e=1,2,3}\pi_{e1998}\overline{w}_{et}$.

28. This condition can also be checked region by region, although the small regional sample size makes the regional estimates of the relative immigrant densities very imprecise. Grouping our regions into 3 or 11 macro-regions show that no re-ranking occurs in any region for values of the elasticity of substitution greater than or equal to, respectively, 0·16 and 0·22 (corresponding to a σ of about $-3{\cdot}5$ and $-4{\cdot}3$).

5.2. *Effects along the wage distribution*

We now turn to our analysis of immigration on the wages of native workers. We commence by estimating the effect of immigration along the distribution of wages. In Table 4, we report results for the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentile of the wage distribution. Columns 1 and 2 present OLS results and Columns 3–6 present IV results, using alternative instruments. Reported results are based on difference estimations. Columns 2, 4, and 6 control, in addition to time effects, for average natives' and immigrants' age and the logarithm of the ratio of natives in each education group to natives with no qualifications. Estimation is based on yearly data for the years 1997–2005 and for 17 regions.

The regression results show a sizeable negative impact of immigration on the lower wage quantiles. According to IV estimates in Column 6, where we use the fourth lag of the ratio of immigrants to natives as instrument and include all controls, an inflow of immigrants of the size of 1% of the native population would lead to a 0·6% decrease at the 5th wage percentile and a 0·5% decrease at the 10th wage percentile. On the other hand, it would lead to a 0·6% increase at the median wage and a 0·4% increase at the 90th percentile. Estimates using as instruments the 1991 immigrant concentration (from the 1991 Census) interacted with year dummies (see Columns 3 and 4) give a similar picture, but with somewhat smaller coefficients and with less precise estimates at the lowest percentiles. Both IV estimates indicate a positive impact of immigration

TABLE 4
Effect of immigration on wage distribution—impact on different wage percentiles

	OLS		IV [1991 immigration share]		IV [four-period lag]	
	First differences		First differences		First differences	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
5th Percentile	−0·165	−0·221	−0·353	−0·340	−0·750	−0·665
	(0·383)	(0·383)	(0·181)	(0·186)	(0·286)	(0·282)
10th Percentile	−0·079	−0·094	−0·217	−0·219	−0·536	−0·516
	(0·231)	(0·237)	(0·109)	(0·115)	(0·173)	(0·175)
25th Percentile	0·175	0·124	0·237	0·305	0·119	0·212
	(0·210)	(0·207)	(0·099)	(0·101)	(0·156)	(0·152)
50th Percentile	0·264	0·234	0·409	0·444	0·615	0·660
	(0·192)	(0·190)	(0·091)	(0·093)	(0·144)	(0·141)
75th Percentile	0·407	0·375	0·441	0·500	0·561	0·617
	(0·210)	(0·207)	(0·099)	(0·101)	(0·156)	(0·152)
90th Percentile	0·341	0·314	0·299	0·340	0·379	0·414
	(0·262)	(0·257)	(0·124)	(0·125)	(0·194)	(0·188)
95th Percentile	0·251	0·230	0·301	0·286	0·387	0·381
	(0·325)	(0·327)	(0·153)	(0·159)	(0·241)	(0·239)
F-stat for significance of excluded instruments			172·06	115·53	156·03	163·71
Partial R^2 for first-stage regression			0·454	0·463	0·322	0·333
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Observations	136	136	136	136	136	136

Notes: Entries are the estimated regression coefficients of the ratio of immigrants to natives in regressions of different natives' wage percentiles on the ratio of immigrants to natives for years 1997–2005. "Other controls" include average natives' and immigrants' age, and the logarithm of the ratio of natives in each education group to natives with no qualifications. Standard errors are reported in parentheses.

around the median wage but a negative effect at the bottom of the wage distribution. According to these estimates, immigration seems to put downward pressure on the lower part of the wage distribution but increases wages at the upper part of the distribution.

We note that the OLS estimates are smaller in absolute magnitude than the IV estimates. This is not what we should expect if immigrants were allocated to regions which experienced positive economic shocks. However, as we point out above, instrumentation removes also measurement error, which leads to a bias towards zero in the estimated parameters.[29] Our results suggest that the measurement error bias is larger in magnitude than the selection bias.[30]

In terms of magnitude, our estimates in Column 6 of Table 4 suggest that each 1% increase in the immigrant–native working-age population ratio led over the period studied to a 0·5% decrease in wages at the 1st decile, a 0·6% increase in wages at the median, and a 0·4% increase in wages at the 9th decile. The average increase in the immigrant–native working-age population ratio over the period considered was about 0·35% per year, whereas the real hourly wage increased over the period by 18p (4·28%) per year at the 1st decile, by 25p (3·25%) per year at the median, and by 53p (3·18%) per year at the 9th decile (in 2005 terms). Therefore, immigration held wages back by 0·7p per hour at the 10th percentile, contributed about 1·5p per hour to wage growth at the median and slightly more than 2p per hour at the 90th percentile.

To obtain a more detailed picture, we have estimated the model at a finer grid of wage percentiles. In Figure 2, we plot the estimated coefficients of regressions from the 5th to the 95th percentile, in intervals of five percentage points for the IV regressions, using the specification in Column 6 of the table. The dotted lines are the 95% confidence interval. The graph shows the negative impact on low-wage percentiles and the positive impact on percentiles further up the wage distribution.[31]

The graph of wage effects illustrated in the figure is strikingly similar to the distribution of immigrants along the native wage distribution, as shown in Figure 1. The wage effects curve is like a mirror image of the observed distribution of recent immigrants over the native wage distribution. The consonance of these two independent pieces of evidence offers strong support for the pattern of effects as suggested by our theoretical model. Overall, these results suggest that immigration tends to stretch the wage distribution, particularly below the median. Our IV coefficients imply that an increase in the immigrant population by about 1% of the native population would increase the 50-10 differential by about one percentage point, but there is hardly any effect of immigration on the wage distribution above the median.

Some previous studies have looked at the effects of immigration on the local wages of different skill groups, defined in terms of occupation (*e.g.* Card, 2001; Orrenius and Zavodny, 2007), education categories (*e.g.* Card and Lewis, 2007), or position in the wage distribution (Card, 1997, 2009a,b). These papers usually find effects going in the same direction as the ones we outline above (a mild stretch in the wage distribution).

29. Aydemir and Borjas (2011) show that the measurement-error-induced attenuation bias becomes exponentially worse as the sample size used to calculate the immigrant concentration declines and that adjusting for attenuation bias can easily double or triple the estimated wage impact of immigration.

30. The standard errors of the IV estimator are smaller than the standard errors of the OLS estimator in differences. The reason is that standard errors, for both OLS and IV, are calculated on the assumption of lack of serial correlation in the residuals of the levels equation so that the differenced equation is assumed to have residuals with a specific pattern of first-order serial correlation (see Arellano and Bond, 1991; Blundell and Bond, 1998). OLS is not efficient given such serial correlation, even under exogeneity of the regressors, and IV may accordingly give lower standard errors.

31. Results using sample weights to calculate wage percentiles show the same pattern of effects across the distribution, though with some weakening of the significance of the negative effects at the very lowest end. As explained in Section 4.2, we prefer not to use the sample weights, which are appropriate to the distribution including immigrants and not simply to natives.

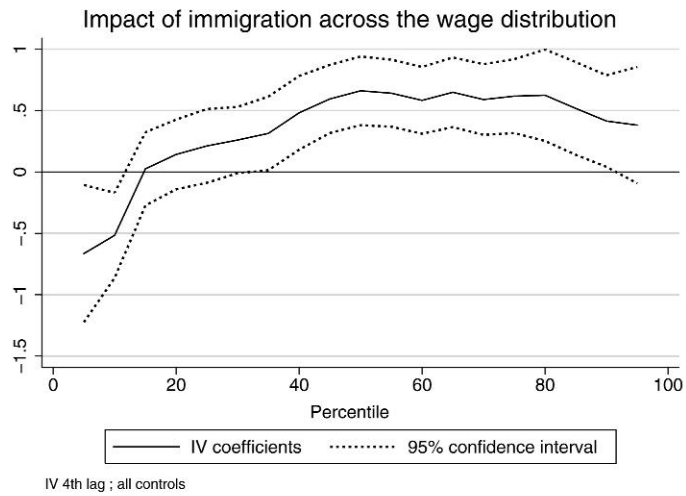

FIGURE 2

The figure reports the estimated IV regression coefficients and the 95% confidence interval from a difference regression of each wage percentile from the 5th to the 95th percentile in intervals of five percentage points on the ratio of immigrants to natives for years 1997–2005 and time dummies. Instrumental variable is the fourth lag of the ratio of immigrants to natives

5.3. *Using information on immigrant densities*

As we explain in Section 2.2, the parameter estimates $\hat{\gamma}_p$ we report above can be interpreted within our model framework as averages of percentile-specific wage effects γ_{prt} across time and region, measuring the impact of an increase in the overall immigrant–native ratio on native log wages at the pth percentile of the native wage distribution. However, we can in principle estimate the relative density of immigrants, averaged across regions and time periods, and check this against the pattern of estimated wage effects $\hat{\gamma}_p$, the patterns of which should be the inverse of each other (see equation (6)). As can be seen in Figures 1 and 2, this visual expectation is confirmed.

We can go further by estimating distributions of immigrants separately for the different regions (distinguishing alternatively between either 3 broadly defined regions or 11 regions[32]). In Figure 3(a) and (b), we plot the relative densities: the overall pattern of immigrant density across the native wage distribution is remarkably similar across regions.[33]

As we discuss above, we can also obtain an estimate of $(\sigma - 1)$, by regressing our estimates $\hat{\gamma}_p$ on estimates of the relative density of immigrants in the native wage distribution, $\hat{\zeta}_p$, assuming perfectly elastic supply of capital ($\phi = 1$). Figure 4 plots the percentile-by-percentile estimated effects of immigration on wages $\hat{\gamma}_p$ (from Figure 2) against estimated relative density of recent immigrants $\hat{\zeta}_p$ as calculated from Figure 1 under the assumption that $\phi = 1$. Fitting a straight line through these points by simple OLS gives a value for the slope of $-1{\cdot}69$ which, taken at face value as an estimate of $(\sigma - 1)$, would suggest an elasticity of substitution of about 0·6.

32. Three regions: North England and Scotland, Greater London, South. Eleven regions: North England, Yorkshire, East Midlands, East Anglia, Greater London, South East, South West, West Midlands, North West, Wales, Scotland.

33. Alternatively, we have computed relative densities for each year, pooling over all regions. The pattern of immigrant density is again very similar across years.

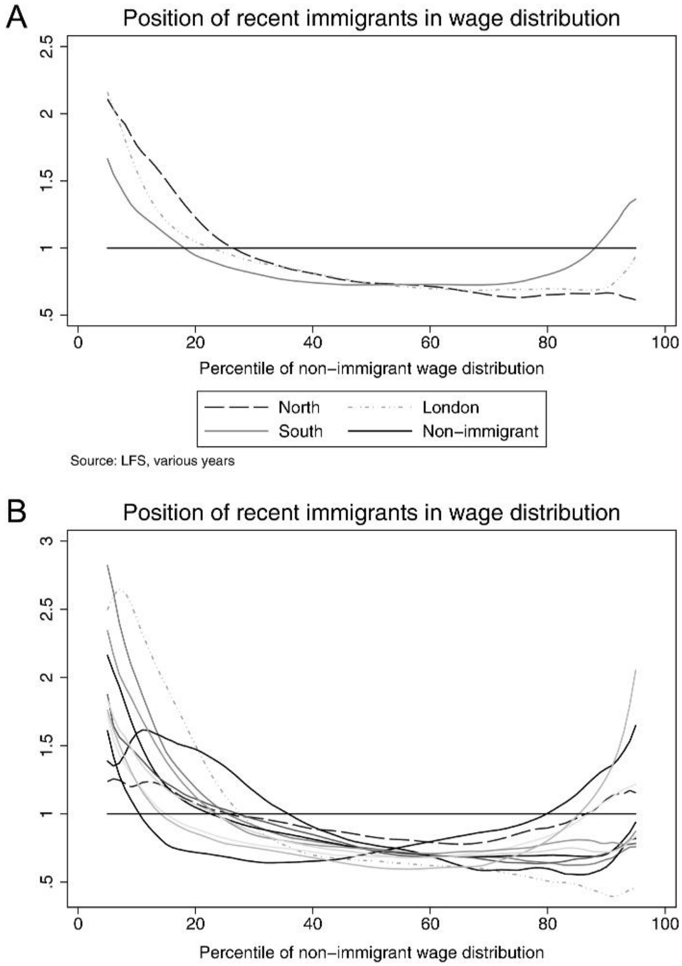

FIGURE 3

The figure shows kernel estimates of the density of immigrants who arrived within the last 2 years in the non-immigrant wage distribution in 3 (panel a) and 11 (panel b) broadly defined U.K. regions. The horizontal line shows as a reference the non-immigrant wage distribution. The kernel estimates are above the horizontal line at wages where immigrants are more concentrated than natives and below the horizontal line at wages where immigrants are less concentrated than natives

5.4. *Immigration and average wages*

In Table 5, we present results of mean regressions from estimating equation (7), using the different measures for average wages which we discuss above. Results are consistent across all specifications and show a positive impact of immigration on natives' average wages throughout.

The coefficients on the wage index (in the third row) and on the robust wage index (in the fourth row) capture most closely the mean impact at fixed skill composition corresponding to our theoretical model (see Section 2). These estimates indicate that an increase in the foreign -born population of the size of 1% of the native population leads to an increase of between 0·1% and 0·3% in average wages. As the average yearly increase in the immigrant–native ratio over our sample period (1997–2005) was about 0·35% and the average real wage growth just over 3%, immigration contributed about 1·2–3·5% to annual real wage growth. Positive overall wage

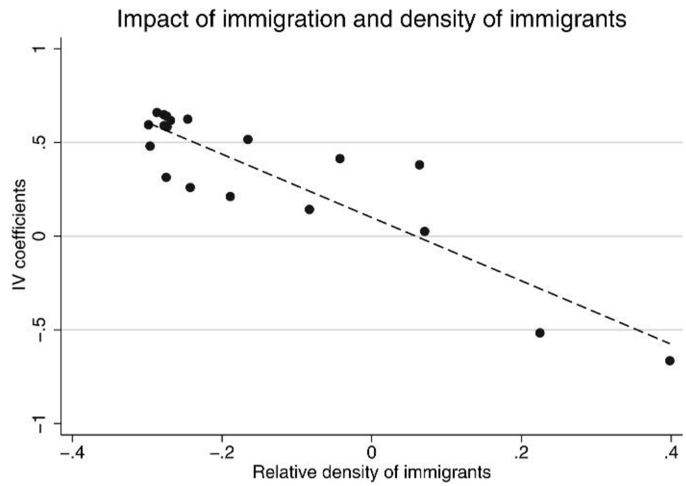

FIGURE 4

The figure plots the estimated coefficients for the effect of immigration at every fifth percentile of the native wage distribution (reported in Figure 2) versus the relative density of recent immigrants and natives at that percentile. The inverse of the slope of the line fitted through these points is an estimate of the elasticity of substitution between different labour types

TABLE 5

Effect of immigration on average wages

	OLS		IV [1991 immigration share]		IV [four-period lag]	
	First differences		First differences		First differences	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Average	0·410	0·389	0·213	0·256	0·428	0·465
	(0·187)	(0·181)	(0·088)	(0·088)	(0·138)	(0·133)
Robust average	0·296	0·272	0·268	0·302	0·356	0·396
	(0·156)	(0·153)	(0·074)	(0·074)	(0·116)	(0·112)
Wage index	0·322	0·311	0·100	0·132	0·306	0·338
	(0·168)	(0·169)	(0·079)	(0·083)	(0·124)	(0·124)
Robust index	0·228	0·215	0·168	0·192	0·270	0·301
	(0·137)	(0·139)	(0·064)	(0·068)	(0·101)	(0·102)
F-stat for significance of excluded instruments			172·06	115·53	156·03	163·71
Partial R^2 for first-stage regression			0·454	0·463	0·322	0·333
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	Yes	No	Yes	No	Yes
Observations	136	136	136	136	136	136

Notes: Entries are the estimated regression coefficients of the ratio of immigrants to natives in regressions of different measures of natives' average wages on the ratio of immigrants to natives for years 1997–2005. Robust average wages are computed by trimming the wage distribution at the (region- and year-specific) top and bottom percentile. The wage index is the weighted log sum of the average wage of each education group, using time-invariant weights. Its robust version uses the trimmed distribution to compute education-specific averages. "Other controls" include average natives' and immigrants' age and the logarithm of the ratio of natives in each education group to natives with no qualifications. Standard errors are reported in parentheses.

effects are also found by other studies: for instance, Friedberg (2001) shows for Israel in the early 1990s that an increase in the immigrant–native ratio in an occupation of one percentage point lead to about a 0·7% increase in occupational wages. Card's (2009a) estimates for the U.S. in 2000 imply an even larger effect of immigration on average wages.

How can we explain the positive impact of immigration on mean native wages? A first possibility is that a surplus arises because immigration takes the economy down its labour demand curve. Positive effects on native wages are compatible with a standard equilibrium model with differentiated labour and elastically supplied capital, as we discuss in Section 2.1. Such an effect is second order however—the marginal impact is zero.

To investigate whether the positive mean wage effects of the magnitude found in our analysis can be accounted for by an equilibrium surplus argument, we have simulated our model for the distribution of immigrants we observe in the data and established the overall effects on wages for different sets of model parameters; we provide details in the Online Appendix OA.1. Although these simulations lead to unambiguously positive mean native wage effects if we allow for perfectly elastic supply of capital, for the distribution of immigrant wages observed in our data, the size of this surplus is always smaller than (and about 1/6 of) the positive mean wage effect that we find. The divergence between the native and immigrant skill distributions may be more extreme than Figure 1 suggests if immigrants differ across labour types *within* percentiles, rather than in their distribution across percentiles of the native wage distribution. This argument is similar to that made by Ottaviano and Peri (2012) regarding the imperfect substitutability of native and immigrant labour within observed skill cells. However, it remains difficult to argue that the conventional equilibrium immigration surplus accounts alone for mean wage effects of the magnitude estimated.

There are at least two alternative explanations. The first is similar to Borjas's (2001) argument that immigration may "grease the wheels" of the labour market: sluggish responsiveness of the native labour allocation to economic signals may create scope for immigration to realize efficiency gains. If (as Borjas assumes) immigrants are paid the value of their marginal product, the associated gains are captured by immigrants rather than native labour and cannot explain a positive wage gain for natives. But if wages deviate from the values of marginal products because, for instance, labour market agreements impose equality of wages across regions or occupations or because wages are rigid and local demand conditions lead to differences in the productivity of identical labour, immigration would generate a surplus if there were skill shortages which attracted strong immigrant inflows. To assess the possible magnitude in our case, we use information on the observed divergence in wage distributions to bound the magnitude of wage gaps required to rationalize the magnitude of surplus observed (see Online Appendix OA.2). These calculations suggest a need for wage gaps between observed and equilibrium wage which is around twice the estimated average wage effect.

A second alternative explanation requires no divergence between wages and marginal products in the native population and is simply that wages paid to immigrants are below their marginal product, perhaps because of allocation to jobs inappropriate to their true skills. To the extent that underpayment may be related to downgrading, one possible approach to assessing the plausibility of this explanation would be to compare immigrant wages with those earned by natives with similar levels of education and age as estimated by wage regressions in the native population and calculating the surplus as $\sum_i (\tilde{w}_i - w_i)\pi_i^0$.[34] This gives a surplus per immigrant

34. We run separate native log-wage regressions by gender and year and include as regressors five age categories (16/25, 26/35, 36/45, 46/55, 56/65), four educational categories, based on age at which individuals left full-time education (before 16, 16/18, 19/20, after 20), interactions between the two, a dummy for London residents, and quarter dummies. Based on these estimated coefficients, we predict for every immigrant the wage of an identical native

equal to about 0·11 of the mean native wage (see Online Appendix OA.3). This is an appreciable fraction of the positive effect we are seeking to explain, which ranges between 0·1 and 0·34.

6. DISCUSSION AND CONCLUSIONS

Upon arrival, immigrants may work in jobs or occupations that do not correspond to their observed skills. We demonstrate that this "downgrading" is substantial in the case of the U.K. and positions recent immigrants at different percentiles of the native wage distribution than where we would expect them based on their observed skills. Based on a nested CES framework with a large number of skill groups and capital, we derive an estimator that determines the effect of immigration along the *distribution* of native wages. Our approach is flexible in the sense that it does not necessitate pre-allocation of immigrants to particular groups and allows immigration to have differential effects along the native wage distribution, with some workers gaining and others losing.

The results we obtain from regressing wage changes at different percentiles of immigration intensity are remarkably in line with what we should expect given the actual density of immigrants along the distribution of natives and what our model suggests. We find that immigration leads to a decrease in wages at those parts of the distribution where the relative density of immigrants is higher than the relative density of natives. On the other hand, it leads to an increase in native wages at parts of the distribution where the opposite is the case. We explore the possibility of incorporating information on location of immigrants in the wage distribution into the estimation procedure.

On average, over the distribution of natives, we find that immigration, over the period considered, leads to a slight increase in average wages. It is difficult to explain the magnitude of the effect through a conventional immigrant surplus story. However, the possibility that immigrants receive less than their marginal value product either because of initial mismatch or because of downgrading can explain a substantial part of this overall wage effect.

Our analysis adds important insights to the academic debate on the impact of immigration. First, we believe that estimates of wage effects along the distribution of native wages are useful and important parameters as they reveal the impact immigration has on workers positioned across the distribution. These effects may be masked if concentrating on mean effects or on effects between skill groups. Further, the approach we suggest has the advantage that it does not require any pre-allocation of immigrants to skill groups—which can be problematic if immigrants downgrade upon arrival. Finally, the parameters have a clear-cut interpretation as they translate the relative density of immigrants along the native distribution into effects on wages at that part of the distribution. As we show, the correspondence between these two independent parts of evidence is remarkable.

APPENDIX A: GENERAL THEORY

We start with as general a setting as possible. Suppose the economy consists of many firms producing many outputs using many inputs. Specifically, suppose the ith firm produces outputs $\boldsymbol{y}_{\mathbf{i}}$ using capital inputs $\boldsymbol{k}_{\mathbf{i}}$ and labour inputs $\boldsymbol{l}_{\mathbf{i}}$, where each of these can be a vector of any length, according to technological restrictions specifying that the output plan $(\boldsymbol{y}_{\mathbf{i}}, \boldsymbol{k}_{\mathbf{i}}, \boldsymbol{l}_{\mathbf{i}})$ lies in some technology set. We assume that technology obeys constant returns to scale, outputs are sold at fixed world prices $\boldsymbol{p}$, and capital inputs are elastically supplied at world capital prices $\boldsymbol{r}$. Wages are denoted $\boldsymbol{w}$.

Individual firms maximize profits taking prices as given so that economy-wide profit $\boldsymbol{p}\cdot\boldsymbol{y}-\boldsymbol{r}\cdot\boldsymbol{k}-\boldsymbol{w}\cdot\boldsymbol{l}$ is maximized at the given prices where $\boldsymbol{y}=\Sigma_i \boldsymbol{y}_{\mathbf{i}}$, $\boldsymbol{k}=\Sigma_i \boldsymbol{k}_{\mathbf{i}}$, and $\boldsymbol{l}=\Sigma_i \boldsymbol{l}_{\mathbf{i}}$. Equilibrium profits of zero are assured by the assumption of constant returns to scale.

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individual and take the difference between this and the actual wage. We then add up all the differences and express this as a share of the total native wage bill. The obtained value is then rescaled by dividing by the ratio of immigrants to natives in the population.

Wages are determined to equate aggregate demand for labour $\boldsymbol{l}$ to aggregate supply. Before immigration, aggregate supply is $\boldsymbol{n^0}$, where $\boldsymbol{n^0}$ is native labour and after immigration it is $\boldsymbol{n} = \boldsymbol{n^0} + \boldsymbol{n^1}$, where $\boldsymbol{n^1}$ is immigrant labour.

Let $\boldsymbol{y^0}$ and $\boldsymbol{k^0}$ be the equilibrium outputs and capital inputs and $\boldsymbol{w^0}$ be the equilibrium wages before immigration and let $\boldsymbol{y}$ and $\boldsymbol{k}$ be the equilibrium outputs and capital inputs and $\boldsymbol{w}$ be the equilibrium wages after immigration.

By the assumption, given constant returns to scale, that profits are maximized at zero before and after immigration

$$\boldsymbol{0} = \boldsymbol{p}\cdot\boldsymbol{y^0} - \boldsymbol{r}\cdot\boldsymbol{k^0} - \boldsymbol{w^0}\cdot\boldsymbol{n^0} \geq \boldsymbol{p}\cdot\boldsymbol{y} - \boldsymbol{r}\cdot\boldsymbol{k} - \boldsymbol{w^0}\cdot\boldsymbol{n} \tag{A.1}$$

and

$$\boldsymbol{0} = \boldsymbol{p}\cdot\boldsymbol{y} - \boldsymbol{r}\cdot\boldsymbol{k} - \boldsymbol{w}\cdot\boldsymbol{n} \geq \boldsymbol{p}\cdot\boldsymbol{y^0} - \boldsymbol{r}\cdot\boldsymbol{k^0} - \boldsymbol{w}\cdot\boldsymbol{n^0}. \tag{A.2}$$

Hence, by subtraction of the rightmost expression in equation (A.2) from the leftmost expression in equation (A.1)

$$\Delta\boldsymbol{w}\cdot\boldsymbol{n^0} \geq \boldsymbol{0}, \tag{A.3}$$

which is to say the average wage of natives cannot fall. If wages change at all, average native wages must rise. This is the immigration surplus. It arises because demand curves for labour cannot slope up and immigrants are therefore paid no more than the value of their addition to output. Given that profits are zero, the resulting surplus is returned to existing factors and, given perfectly elastic supply of capital, payments to existing labour must rise.[35] Furthermore, by subtraction of the leftmost expression in equation (A.2) from the rightmost expression in equation (A.1),

$$\Delta\boldsymbol{w}\cdot\boldsymbol{n} \leq \boldsymbol{0}. \tag{A.4}$$

Note here that if $\boldsymbol{n}$ is proportional to $\boldsymbol{n^0}$, so that immigrant skill composition is the same as that in the existing population, then equations (A.3) and (A.4) can both be true only if $\Delta\boldsymbol{w} = \boldsymbol{0}$ so there are necessarily no changes to equilibrium wages (and consequently also no surplus). This is not the only case in which wage changes are zero. If the number of output types produced is the same as the number of labour types before and after immigration, then immigration should also lead to no change in equilibrium wages (see Leamer and Levinsohn, 1995).

Further, by subtraction of equation (A.3) from equation (A.4),

$$\Delta\boldsymbol{w}\cdot\boldsymbol{n^1} \leq \boldsymbol{0}. \tag{A.5}$$

Hence, given $\boldsymbol{n^1} > \boldsymbol{0}$, if wages do change, then equilibrium wages must fall for some types. The inequality in equation (A.5) shows the sense in which these falls must tend to be greater where immigration is most intense.

APPENDIX B: CES PRODUCTION

Wage determination

Production technology takes the nested CES form

$$\begin{aligned} y &= [\beta H^s + (1-\beta)K^s]^{1/s}, \\ H &= N\left[\sum_i \alpha_i(\pi_i^0 + \pi_i^1 m)^\sigma\right]^{1/\sigma}. \end{aligned} \tag{B.1}$$

Equilibrium values of wages ω_i and return to capital ρ are given by the value of the respective marginal products

$$\ln\omega_i = \ln\beta\alpha_i + (\sigma-1)\ln(\pi_i^0 + \pi_i^1 m) + (1-\sigma)\ln\left(\frac{H}{N}\right) + \left(\frac{1}{s}-1\right)\ln\left[\beta + (1-\beta)\left(\frac{K}{H}\right)^s\right], \tag{B.2}$$

$$\ln\rho = \ln(1-\beta) + (s-1)\ln\left(\frac{K}{H}\right) + \left(\frac{1}{s}-1\right)\ln\left[\beta + (1-\beta)\left(\frac{K}{H}\right)^s\right]. \tag{B.3}$$

35. If capital is less than perfectly elastically supplied, then some of the surplus may go to capital and it can be said only that existing inputs as a whole gain.

First-order effect of immigration on the wage distribution

Differentiating these expressions gives

$$\frac{d\ln w_i}{dm} = (\sigma-1)\frac{\pi_i^1}{\pi_i^0+\pi_i^1 m} + (1-\sigma)\frac{d\ln H}{dm} + (1-s)(1-\psi)\left(\frac{d\ln K}{dm} - \frac{d\ln H}{dm}\right),$$

$$\frac{d\ln H}{dm} = \sum_i \frac{\alpha_i \pi_i^1(\pi_i^0+\pi_i^1 m)^{\sigma-1}}{\sum_j \alpha_j(\pi_j^0+\pi_j^1 m)^{\sigma}} = \sum_i \omega_i \frac{\pi_i^1}{\pi_i^0+\pi_i^1 m},$$

$$\frac{d\ln\rho}{dm} = -(1-s)\psi\left(\frac{d\ln K}{dm} - \frac{d\ln H}{dm}\right),$$

where $\omega_i = \frac{\alpha_i(\pi_i^0)^\sigma}{\sum_j \alpha_j(\pi_j^0)^\sigma}$ is share of the ith type in the labour aggregate H^σ and $\psi = \frac{\beta H^s}{\beta H^s+(1-\beta)K^s}$ is share of labour in the CES aggregate y^s.

Letting $\frac{d\ln K}{dm} = \theta\frac{d\ln\rho}{dm}$, where θ is the elasticity of supply of capital, we can substitute into the expression for $\frac{d\ln\rho}{dm}$ to get

$$\frac{d\ln\rho}{dm} = \frac{(1-s)\psi}{1+(1-s)\psi\theta}\frac{d\ln H}{dm}$$

and thus

$$\begin{aligned}
\frac{d\ln w_i}{dm} &= (\sigma-1)\frac{\pi_i^1}{\pi_i^0+\pi_i^1 m} + (1-\sigma)\frac{d\ln H}{dm} - \frac{1}{\psi}(1-\psi)\frac{d\ln\rho}{dm}\\
&= (\sigma-1)\left(\frac{\pi_i^1}{\pi_i^0+\pi_i^1 m} - \left[1-\frac{(1-s)(1-\psi)}{1+(1-s)\psi\theta}\frac{1}{(\sigma-1)}\right]\frac{d\ln H}{dm}\right)\\
&= (\sigma-1)\left(\frac{\pi_i^1}{\pi_i^0+\pi_i^1 m} - \phi\sum_j \frac{\alpha_j(\pi_j^0+\pi_j^1 m)^\sigma}{\sum_k \alpha_k(\pi_k^0+\pi_k^1 m)^\sigma}\frac{\pi_j^1}{\pi_j^0+\pi_j^1 m}\right),
\end{aligned}$$

where $\phi = 1+\left[\frac{(1-s)(1-\psi)}{1+(1-s)\psi\theta}\right]\frac{1}{\sigma-1} \leq 1$. Note that $\phi = 1$ if there is perfectly elastic supply of capital ($\theta = \infty$), perfect substitutability of capital and labour ($s = 1$), or capital share is zero ($\psi = 1$).

If we set $m = 0$, then we get

$$\left.\frac{d\ln w_i}{dm}\right|_{m=0} = (\sigma-1)\left(\frac{\pi_i^1}{\pi_i^0} - \phi\sum \omega_j\frac{\pi_j^1}{\pi_j^0}\right). \tag{B.3}$$

First-order effect of immigration on the mean native wage

From equation (B.2), at $m = 0$, $w_i\pi_i^0 = \omega_i\bar{w}^0$, where $\bar{w}^0$ denotes the mean wage at $m = 0$. Hence, the first-order effect of immigration on mean wages in the preexisting population is

$$\left.\frac{d\sum w_i\pi_i^0}{dm}\right|_{m=0} = \sum_i \pi_i^0 w_i\left.\frac{d\ln w_i}{dm}\right|_{m=0} = (\sigma-1)(1-\phi)\bar{w}^0\sum\omega_i\frac{\pi_i^1}{\pi_i^0} \leq 0. \tag{B.4}$$

This is non-positive since $\sigma \leq 1$ and $\phi \leq 1$ and equals zero iff $\phi = 1$ or $\sigma = 1$.

First-order effect of immigration on the wage of competing labour

The first-order effect on mean wages of a population composed similarly to immigrants is

$$\begin{aligned}
\left.\frac{d\sum w_i\pi_i^1}{dm}\right|_{m=0} &= \sum_i \frac{\pi_i^1}{\pi_i^0}\pi_i^0 w_i\left.\frac{d\ln w_i}{dm}\right|_{m=0}\\
&= (\sigma-1)\bar{w}^0\left[\sum\omega_i\left(\frac{\pi_i^1}{\pi_i^0}\right)^2 - \phi\left(\sum\omega_i\frac{\pi_i^1}{\pi_i^0}\right)^2\right] \leq 0. \qquad \text{(B.5)}
\end{aligned}$$

In this case, non-positivity follows from the Cauchy–Schwarz inequality, given $\phi \leq 1$, since

$$\sum \omega_i \left(\frac{\pi_i^1}{\pi_i^0}\right)^2 - \phi\left(\sum \omega_i \frac{\pi_i^1}{\pi_i^0}\right)^2 \geq \sum \omega_i \left(\frac{\pi_i^1}{\pi_i^0}\right)^2 - \left(\sum \omega_i \frac{\pi_i^1}{\pi_i^0}\right)^2 \geq 0,$$

and the first-order effect is zero iff either $\phi = 1$ and $\pi_i^1 = \pi_i^0$ for all i or $\sigma = 1$.

Second-order effect of immigration on the mean native wage

In the special case that $\phi = 1$, it is necessary to turn to second-order terms in order to sign the effect of small amounts of immigration:

$$\sum \pi_i^0 \frac{d^2 w_i}{dm^2} = \sum w_i \pi_i^0 \left[\frac{d^2 \ln w_i}{dm^2} + \left(\frac{d \ln w_i}{dm}\right)^2\right]. \tag{B.6}$$

Given $\phi = 1$,

$$\frac{d \ln w_i}{dm} = (\sigma - 1)\left(\frac{\pi_i^1}{\pi_i^0 + \pi_i^1 m} - \sum_j \frac{\alpha_j (\pi_j^0 + \pi_j^1 m)^\sigma}{\sum_k \alpha_k (\pi_k^0 + \pi_k^1 m)^\sigma} \frac{\pi_j^1}{\pi_j^0 + \pi_j^1 m}\right)$$

and therefore

$$\frac{d^2 \ln w_i}{dm^2} = (\sigma - 1)\left(\begin{array}{l} -\left(\frac{\pi_i^1}{\pi_i^0 + \pi_i^1 m}\right)^2 - (\sigma - 1)\sum_j \frac{\alpha_j (\pi_j^0 + \pi_j^1 m)^\sigma}{\sum_k \alpha_k (\pi_k^0 + \pi_k^1 m)^\sigma}\left(\frac{\pi_j^1}{\pi_j^0 + \pi_j^1 m}\right)^2 \\ + \sigma\left(\sum_j \frac{\alpha_j (\pi_j^0 + \pi_j^1 m)^\sigma}{\sum_k \alpha_k (\pi_k^0 + \pi_k^1 m)^\sigma} \frac{\pi_j^1}{\pi_j^0 + \pi_j^1 m}\right)^2 \end{array}\right),$$

$$\left(\frac{d \ln w_i}{dm}\right)^2 = (\sigma - 1)^2\left(\begin{array}{l} \left(\frac{\pi_i^1}{\pi_i^0 + \pi_i^1 m}\right)^2 - 2\left(\frac{\pi_i^1}{\pi_i^0 + \pi_i^1 m}\right)\sum_j \frac{\alpha_j (\pi_j^0 + \pi_j^1 m)^\sigma}{\sum_k \alpha_k (\pi_k^0 + \pi_k^1 m)^\sigma} \frac{\pi_j^1}{\pi_j^0 + \pi_j^1 m} \\ + \left(\sum_j \frac{\alpha_j (\pi_j^0 + \pi_j^1 m)^\sigma}{\sum_k \alpha_k (\pi_k^0 + \pi_k^1 m)^\sigma} \frac{\pi_j^1}{\pi_j^0 + \pi_j^1 m}\right)^2 \end{array}\right).$$

Substituting into equation (B.6), summing and simplifying for the case $m = 0$, gives

$$\begin{aligned} \sum \pi_i^0 \frac{d^2 w_i}{dm^2}\bigg|_{m=0} &= \sum w_i \pi_i^0 \left[\frac{d^2 \ln w_i}{dm^2} + \left(\frac{d \ln w_i}{dm}\right)^2\right]\bigg|_{m=0} \\ &= (1 - \sigma)\bar{w}^0 \left[\sum \omega_i \left(\frac{\pi_i^1}{\pi_i^0}\right)^2 - \left(\sum \omega_i \frac{\pi_i^1}{\pi_i^0}\right)^2\right] \geq 0, \end{aligned} \tag{B.7}$$

which is positive provided the skill composition of immigrants differs from the preexisting population, again by the Cauchy–Schwarz inequality. Furthermore, the size of the second-order effect on mean wages is evidently greater the greater the dissimilarity.

APPENDIX C

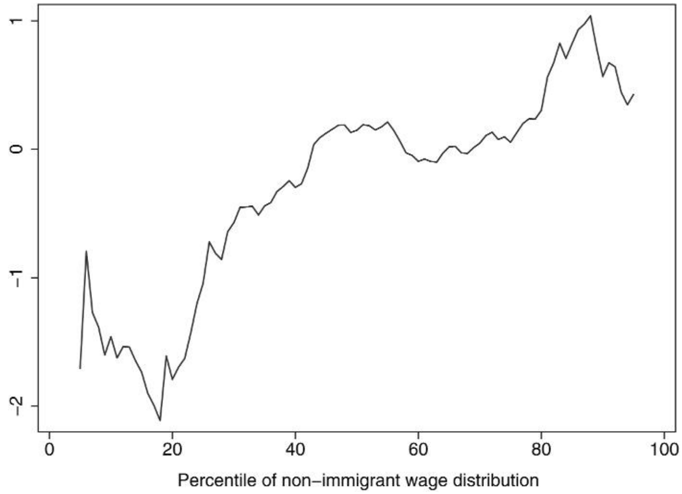

FIGURE A1

The figure reports for each percentile p of the native wage distribution the ratio of the difference between the density of recent immigrants at p and at $p-1$ and the difference in log wages at p and $p-1$

TABLE A1
Test for serial correlation in wage variables

Dependent variable	M1	M2
Average wage	−2·63 $p = 0{\cdot}009$	−0·5 $p = 0{\cdot}615$
Robust average wage	−2·14 $p = 0{\cdot}032$	−2·21 $p = 0{\cdot}027$
Wage index	−2·74 $p = 0{\cdot}006$	−0·40 $p = 0{\cdot}687$
Robust wage index	−2·22 $p = 0{\cdot}026$	−1·82 $p = 0{\cdot}068$
5th Percentile	−3·73 $p = 0{\cdot}000$	−0·92 $p = 0{\cdot}357$
10th Percentile	−3·96 $p = 0{\cdot}000$	−0·22 $p = 0{\cdot}829$
25th Percentile	−3·83 $p = 0{\cdot}000$	0·37 $p = 0{\cdot}710$
50th Percentile	−2·31 $p = 0{\cdot}021$	−2·96 $P = 0{\cdot}003$
75th Percentile	−1·27 $p = 0{\cdot}203$	−3·86 $p = 0{\cdot}000$
90th Percentile	−2·84 $p = 0{\cdot}004$	−1·75 $p = 0{\cdot}080$
95th Percentile	−3·38 $p = 0{\cdot}001$	−0·81 $p = 0{\cdot}417$

Notes: The table reports Arellano–Bond tests for first- (M1) and second- (M2) order serial correlation based on residuals from the first differenced equation with all control variables, estimated using the fourth lag of immigrant–native ratio as IV. The test is asymptotically distributed as a normal.

TABLE A2
Effect of immigration on log average natives' wages, different instruments

Instrumental variable	Average wage (1)	Robust average (2)
4th lag of immigrant–native ratio	0·428	0·356
	(0·138)	(0·116)
14th lag of immigrant–native ratio	0·369	0·326
	(0·136)	(0·114)
1991 immigrant–native ratio (Census 1991)	0·213	0·268
	(0·088)	(0·074)
1981 immigrant–native ratio (Census 1981)	0·193	0·258
	(0·093)	(0·077)
Change 1991 − 1981	0·284	0·300
	(0·082)	(0·068)
Predicted inflow by ethnic group (LFS 91)	0·411	0·320
	(0·168)	(0·140)
Predicted inflow by ethnic group (LFS 85)	0·326	0·266
	(0·186)	(0·155)
Predicted inflow by ethnic group (LFS 81)	0·332	0·291
	(0·172)	(0·144)

Notes: Entries are the estimated IV regression coefficients of the ratio of immigrants to natives in regressions of log average regional wages and robust log average regional wages on the ratio of immigrants to natives for the years 1997–2005. The instrumental variable used is described in the first column. Robust average wages are computed by trimming the wage distribution at the (region- and year-specific) top and bottom percentiles. Standard errors are reported in parentheses.

TABLE A3
Descriptive statistics

Variable	Mean	S.D.
Log wages, all natives		
Average hourly pay	2·212	0·138
Robust average hourly pay	2·182	0·136
Wage index	2·194	0·131
Robust wage index	2·169	0·128
Natives' log-wage percentiles		
5th	1·267	0·148
10th	1·433	0·129
25th	1·678	0·131
50th	2·022	0·132
75th	2·413	0·134
90th	2·763	0·139
95th	2·97	0·152
Immigrant–native ratio	0·086	0·107
Annual change in immigrant–native ratio	0·003	0·008
Average natives' age	40·331	0·944
Average immigrants' age	39·329	1·992
ln high education/low education	−1·659	0·378
ln intermediate educate/low educaation	−1·048	0·278

Notes: Entries are the mean value and the standard deviation (S.D.) of the variables used in the analysis, across all regions and years 1997–2005. Wages are expressed in 2005 pounds, using the 2005 Consumer Prices index. *Source:* LFS 1997–2005.

TABLE A4
Descriptive statistics on immigrants' inflow

Years	Mean (%)	S.D. (%)	Minimum (%)	Maximum (%)
1997–1998	0·25	0·79	−1·21	2·65
1998–1999	0·02	0·50	−1·09	0·74
1999–2000	0·15	0·98	−0·68	3·82
2000–2001	0·45	0·66	−0·47	2·26
2001–2002	0·43	0·87	−0·59	3·02
2002–2003	0·26	0·45	−0·71	1·28
2003–2004	0·43	0·72	−0·47	2·60
2004–2005	0·82	0·57	−0·32	1·86
Average 1997–2005	0·35			
1997–2005	2·81	3·44	−0·27	15·55

Notes: Entries are the annual mean, standard deviation (S.D.), minimum, and maximum across all regions of the change in immigrant–native ratio for the years 1997–2005. The last row reports the mean, S.D., minimum, and maximum across all regions of the 1997–2005 change in immigrant–native ratio. *Source:* LFS, 1997–2005.

Acknowledgments. We are grateful to the Low Pay Commission, the ESRC (grant RES-000-23-0332), and the NORFACE programme on migration for funding this research. We are also grateful to George Borjas, David Card, Andrew Chesher, and Simon Lee for helpful comments and discussions and to the editor and three anonymous referees for constructive comments.

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