

Companion Appendix to

The Impact of Immigration:

Why Do Studies Reach Such Different Results?

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1. Overview

In this appendix we provide formal derivations and a more technical discussion of our article “The Impact of Immigration: Why Do Studies Reach Such Different Results?” The appendix is self-contained, although the reader may find it useful to refer to the article where we keep the discussion informal and intuitive. The appendix follows the same basic structure as our article. We begin with a more formal discussion of the main empirical approaches used in the literature to estimate the wage effects of immigration (Section 2). We then present the canonical model used in the literature in Section 3, and interpret the wage estimates obtained from different empirical approaches through the lens of the model, first assuming inelastic native labor supply (Section 3.2), then allowing for constant (Section 3.3) and heterogeneous elasticities of labor supply (Section 3.4). In Section 4, we first present a method to impute the effective experience and education group of immigrants under immigrant downgrading (Section 4.1), and then illustrate how downgrading affects estimates of the relative wage impact of immigration in the mixture and national skill cell approach (Section 4.2). In a final step, we turn to approaches that explicitly estimate the underlying parameters of the canonical model and use that model to predict the wage effects of immigration, as in for example Ottaviano and Perio (2012) and Manacorda, Manning and Wadsworth (2012).

2. Estimation Approaches Used in the Literature

2.1 The National Skill-Cell Approach: Variation in the Immigration Shock across Skill Cells

The baseline estimation equation in Borjas (2003), or other papers adopting the national skill-cell approach, can be written as a first difference equation:

$$\Delta \log w_{gat} = \theta^{skill} \Delta p_{gat} + \Delta \pi_t + (s_g \times \Delta \pi_t) + (x_a \times \Delta \pi_t) + \Delta \varphi_{gat} \quad (2.1)$$

where $\Delta \log w_{gat}$ denotes the change in native wage (in logs) in education group g , experience group a and time t , Δp_{gat} denotes the education-experience specific immigration shock, defined as the difference in the ratio of immigrants to all labor in each education-experience group ga between two time periods, and the error term $\Delta \varphi_{gat}$ captures other sources for education-experience specific wage growth. The variables s_g , x_a , and π_t are vectors of education, experience and time fixed effects. In the case of two time periods, two education groups and two experience groups, the parameter θ^{skill} can be interpreted as a triple difference estimator, where differences are taken over time, over education groups, and over experience groups. To see this, first compute the difference in wage changes between inexperienced (subindex I) and experienced (subindex E) native workers in an education group to cancel out general and education-specific time effects $\Delta \pi_t + (s_g \times \Delta \pi_t)$:

$$\Delta \log w_{gI} - \Delta \log w_{gE} = \theta^{skill} (\Delta p_{gI} - \Delta p_{gE}) + (x_I \times \Delta \pi_t) - (x_E \times \Delta \pi_t) + \Delta \varphi_{gI} - \Delta \varphi_{gE}$$

Next, further difference between education groups (where L denotes “low education” and H denotes “high education”) to cancel out experience-specific time effects $(x_a \times \Delta \pi_t)$:

$$\begin{aligned} & (\Delta \log w_{LI} - \Delta \log w_{LE}) - (\Delta \log w_{HI} - \Delta \log w_{HE}) \\ &= \theta^{skill} ((\Delta p_{LI} - \Delta p_{LE}) - (\Delta p_{HI} - \Delta p_{HE})) + (\Delta \varphi_{LI} - \Delta \varphi_{LE}) - (\Delta \varphi_{HI} - \Delta \varphi_{HE}). \end{aligned}$$

Our paper is about the correct specification of empirical models and the interpretation of the estimated parameters, not about empirical identification. We assume therefore that the allocation of immigrants to these sub-labor markets is (conditionally) independent of shocks to wages or employment of native workers. Specifically, with the assumption that $(\Delta\varphi_{LI} - \Delta\varphi_{LE}) - (\Delta\varphi_{HI} - \Delta\varphi_{HE}) = 0$ we have

$$\theta^{skill} = \frac{(\Delta\log w_{LI} - \Delta\log w_{LE}) - (\Delta\log w_{HI} - \Delta\log w_{HE})}{(\Delta p_{LI} - \Delta p_{LE}) - (\Delta p_{HI} - \Delta p_{HE})}. \quad (2.2)$$

The parameter θ^{skill} therefore identifies the relative effect of immigration by experience and answers the question: “How does immigration affect native wages of experienced relative to inexperienced workers in the same education group?”

2.2 The Pure Spatial Approach: Variation in the Total Immigration Shock across Regions

In many studies that exploit spatial variation in immigrant inflows, the log wage changes of natives in education group g and experience group a in region r are related to the *total* region-specific immigration shock (defined as the ratio of all immigrants entering the region and all natives in that region), controlling for nation-wide education-experience specific time trends ($s_{ga} \times \Delta\pi_t$):

$$\Delta\log w_{gart} = \theta_{ga}^{spatial} \Delta p_{rt} + s_{ga} \times \Delta\pi_t + \Delta\varphi_{gart}$$

In the case of two time periods and two regions, the coefficient $\theta_{ga}^{spatial}$ can be expressed as a difference-in-differences estimator where differences are taken over time and across regions (here A and B),

$$\Delta\log w_{gaA} - \Delta\log w_{gaB} = \theta_{ga}^{spatial} (\Delta p_A - \Delta p_B) + \Delta\varphi_{gaA} - \Delta\varphi_{gaB}.$$

If $\Delta\varphi_{gaA} - \Delta\varphi_{gaB} = 0$ we thus have

$$\theta_{ga}^{spatial} = \frac{\Delta \log w_{gaA} - \Delta \log w_{gaB}}{\Delta p_A - \Delta p_B}. \quad (2.3)$$

Provided that region B, otherwise identical to region A, did not experience an inflow of immigrants (i.e., $\Delta p_B = 0$) and is not indirectly affected by the immigration shock in region A, this parameter identifies the total effect of immigration on wages of a particular skill group.¹ It answers the question “What is the overall effect of immigration on native wages of a particular education-experience group”.

2.3 The Mixture Approach: Variation in the Immigration Shock across both Skill-Cells and Regions

A third set of papers exploits variation in the immigration shock across both skill-cells and regions, representing a mixture of the pure skill-cell approach and the pure spatial approach. Most papers which fall into this category distinguish only between education (or occupation) groups. These papers then relate the wage change in education group g and region r to the education-specific immigration shock in region r (Δp_{grt}), controlling for education- and region-specific time trends ($s_g \times \Delta \pi_t$ and $s_r \times \Delta \pi_t$):

$$\Delta \log w_{grt} = \theta^{spatial,skill} \Delta p_{grt} + (s_r \times \Delta \pi_t) + (s_g \times \Delta \pi_t) + \Delta \varphi_{grt}$$

In the simple case of two regions A and B, two time periods and two education groups, the parameter $\theta^{spatial,skill}$ can be expressed as a triple difference estimator, where differences are taken over time, across regions and across education, such that

$$\theta^{spatial,skill} = \frac{(\Delta \log w_{LA} - \Delta \log w_{HA}) - (\Delta \log w_{LB} - \Delta \log w_{HB})}{(\Delta p_{LA} - \Delta p_{HA}) - (\Delta p_{LB} - \Delta p_{HB})}. \quad (2.4)$$

¹ Regions could be indirectly affected, for example if natives react to an inflow of immigrants by leaving affected areas or by not entering them in the first place. Whether such responses are quantitatively important is controversial, see for example Borjas (1999), Card (2001), or Borjas (2006).

This expression highlights that $\theta^{spatial,skill}$ identifies the relative wage effect of immigration by education, by comparing wage changes of low and high skilled workers in one region with those in another region. It answers the question: “How does immigration affect native wages of low skilled relative to high skilled workers?”

3. Interpretation of Relative and Total Effects of Immigration through the Lens of the Canonical Model

3.1 Set-Up

Production Function. We assume a simple Cobb-Douglas production function that combines capital K and labor L into a single output good Y , $Y = AL^{1-\alpha}K^\alpha$. Labor is assumed to be a CES aggregate of different education types, and we distinguish here between low (L_L) and high skilled (L_H) labor only, so that $L = [\theta_L L_L^\beta + \theta_H L_H^\beta]^{1/\beta}$. The elasticity of substitution between low and high skilled workers is given by $1/(1 - \beta)$, and measures the percentage change in the ratio of unskilled workers to skilled workers (L_L/L_H) in response to a given percentage change in the wages of unskilled to skilled workers (w_L/w_H). The higher this elasticity, the more substitutable the two groups are. The two skill types are perfect substitutes (implying an infinite substitution elasticity) if $\beta = 1$.

Within each education group, we allow, similar to Card and Lemieux (2001), inexperienced (L_I) and experienced (L_E) workers to be imperfect substitutes, so that $L_g = [\theta_{gI} L_{gI}^\gamma + \theta_{gE} L_{gE}^\gamma]^{1/\gamma}$, and where $1/(1 - \gamma)$ is the elasticity of substitution between inexperienced and experienced workers within an education group. If $\gamma = 1$, the two groups are perfect substitutes. We assume here that immigrants can be correctly classified to education and experience groups and that within an education-experience group, immigrants and natives are perfect substitutes. We turn to the

possibility of misclassification and imperfect substitutability between immigrants and natives below.

The structure above is the model that underlies e.g. the analysis in Borjas (2003), Manacorda et al. (2012) and Ottaviano and Peri (2012). Additional nests can be added to this structure, as done in the latter two papers that allow for imperfect substitutability between immigrants and natives within education-experience groups. Other papers implicitly assume instead that $\gamma = 1$ and distinguish only between different education groups (see e.g. Altonji and Card 1991, Dustmann et al. 2005, Card and Lewis 2007, Card 2009, Lewis 2011, Glitz 2012).

Capital and Labor Supply. Assume that capital is supplied to the labor market according to $r = K^\lambda$, where r denotes the price of capital and $1/\lambda$ is the elasticity of capital supply. Further assume for simplicity that incoming immigrants supply labor inelastically and that there are no immigrants at baseline (since immigrants and natives are perfect substitutes within education-experience groups, we may think of “natives” as residents which include residing immigrants in the country). The total supply of labor in education-experience group ga may then be written as

$$L_{ga} = L_{ga}^{Im} + L_{ga}^N = L_{ga}^{Im} + f_{ga}(w_{ga})$$

and totally differentiating this expression yields

$$d \log L_{ga} = dI_{ga} + d \log L_{ga}^N = dI_{ga} + \eta_{ga} d \log w_{ga} \quad (3.1)$$

where η_{ga} is the labor supply elasticity of natives in education-experience group ga , here allowed to vary across skill groups, and $dI_{ga} = \frac{dL_{ga}^{Im}}{L_{ga}^N}$ is the education-experience specific immigration shock.

Further note that $d\log L_g = s_{gI}d\log L_{gI} + s_{gE}d\log L_{gE}$, where $s_{ga} = \frac{\theta_{ga}L_{ga}^\gamma}{[\theta_{gI}L_{gI}^\gamma + \theta_{gE}L_{gE}^\gamma]}$ is the contribution of labor type ga to the labor aggregate g in the second nest. Similarly, $d\log L = s_Ld\log L_L + s_Hd\log L_H$, where $s_g = \frac{\theta_gL_g^\beta}{[\theta_LL_L^\beta + \theta_HL_H^\beta]}$ is the contribution of labor type g to the overall labor aggregate in the first nest.

Deriving the Firm's Demand Curve. Firms choose capital and labor by maximizing profits, taking wage rates and the price of capital as given. Assuming that output prices are determined in the world market and are normalized to 1, the first order condition for capital equals

$$\log \alpha A + (\alpha - 1)[\log K - \log L] = \log r$$

Totally differentiate this expression to obtain:

$$(\alpha - 1)[d\log K - d\log L] = d\log r$$

Total differentiation of the capital supply function yields $d\log r = \lambda d\log K$, where $1/\lambda$ is the elasticity of capital supply. Plug this expression into the expression above to obtain:

$$d\log K = \frac{1-\alpha}{1-\alpha+\lambda} d\log L$$

The first order condition for labor of type ga equals:

$$\begin{aligned} \log(1 - \alpha) A + \alpha[\log K - \log L] + \log \theta_g + (\beta - \gamma)[\log L_g - \log L] + \log \theta_{ga} + \\ (\gamma - 1)[\log L_{ga} - \log L] = \log w_{ga} \end{aligned}$$

Totally differentiating this expression yields:

$$\alpha[d\log K - d\log L] + (\beta - \gamma)[d\log L_g - d\log L] + (\gamma - 1)[d\log L_{ga} - d\log L] = d\log w_{ga}$$

Substituting in the expression for $d\log K$ and simplifying, we obtain:

$$d\log w_{ga} = \varphi d\log L + (\beta - 1)(d\log L_g - d\log L) + (\gamma - 1)(d\log L_{ga} - d\log L_g) \quad (3.2)$$

where $\varphi = -\frac{\alpha\lambda}{1-\alpha+\lambda}$ is the slope of the aggregate demand curve.

3.2 Interpretation of Relative and Total Wage Effects of Immigration if Labor Supply is Inelastic

The equilibrium wage and employment responses of an immigration-induced labor supply shock are determined by the intersection of firms' demand curve (equation (3.2)) and the labor supply curve (equation (3.1)). We assume first, as often done in the literature, that natives' labor supply is perfectly inelastic in each education-experience group (i.e., $\eta_{ga} = 0$). With inelastic native labor supply, the only reason why total, education- and education-specific employment L , L_g , and L_{ga} change is because of immigration. Define the education-specific and overall immigration shock measured in efficiency units as

$$d\tilde{I}_g = s_{gI} dI_{gI} + s_{gE} dI_{gE} \quad (3.3)$$

$$d\tilde{I} = s_L d\tilde{I}_L + s_H d\tilde{I}_H \quad (3.4)$$

Because of inelastic native labor supply, $d\log L_{ga} = dI_{ga}$, $d\log L_g = d\tilde{I}_g$, and $d\log L = d\tilde{I}$. Substituting these expressions into equation (3.2), we obtain (see the fourth equation in the main article on p. 11):

$$d\log w_{ga} = \varphi d\tilde{I} + (\beta - 1)(d\tilde{I}_g - d\tilde{I}) + (\gamma - 1)(dI_{ga} - d\tilde{I}_g) \quad (3.5)$$

Consider first the third term on the right hand side in equation (3.5), and suppose that within each education group immigration is relatively inexperienced. This term is then negative when considering wages for inexperienced natives, and positive when considering wages for

experienced natives. Thus, *ceteris paribus*, immigration will lower wages of inexperienced natives and raise wages of experienced natives within each education group.

The second term in this equation captures how changes in immigration disproportionately affect wages of low and high skilled natives. This term will be negative for the education group that is exposed to the larger inflow of immigrants and positive for the other education group, implying wage declines for the former and wage increases for the latter group (holding the other terms constant). Thus, the second and third terms summarize the key insight of the simple competitive model: Immigration will decrease the marginal product and hence wages of native workers most similar to immigrant workers, and may increase the marginal product and wages of native workers most dissimilar to immigrant workers.

Finally, the first term in equation (3.5) captures the wage effects of immigration common to all education and experience groups and can, at an intuitive level, be understood as the slope of the aggregate demand curve. If capital supply is fully elastic, this term disappears and on *average*, wages do not change in response to immigration. If in contrast capital supply is not fully elastic, the direct overall immigration shock pulls down wages of all skill groups in the same way, and an immigration-induced labor supply shock has a negative effect on average wages—as immigration will lead to increases in the rent of capital and re-distribute a share of output from labor to capital. To see this more formally, express the average wage change using CES aggregates as weights as

$$\begin{aligned} d\log w &= s_L d\log w_L + s_H d\log w_H \\ &= s_L (s_{LI} d\log w_{LI} + s_{LE} d\log w_{LE}) + s_H (s_{HI} d\log w_{HI} + s_{HE} d\log w_{HE}) \end{aligned}$$

Substituting in the expressions for $d\log w_{ga}$ from equation (3.5) yields

$$d \log w = \varphi d\tilde{I} = -\frac{\alpha\lambda}{1-\alpha+\lambda} d\tilde{I}$$

The parameter φ approaches zero if capital is infinitely elastic (i.e., $\lambda = 0$) and α if capital is fully inelastic (i.e., $\lambda \rightarrow \infty$). Thus, the capital share in output, α , bounds the overall wage decline in response to immigration.

Based on equation (3.5), it is now straightforward to provide a structural interpretation of the relative and total effects of immigration identified by the three empirical approaches described in the previous section.

3.2.1 National Skill Cell Approach

As explained in Section 2.1, the national skill cell approach pioneered by Borjas (2003) identifies the relative wage effect of immigration by experience within education groups, and any effects of immigration common to all education and experience groups, and any effects of immigration common to all experience groups within education groups are differenced out. Put differently, in the empirical specification underlying the national skill cell approach the total and the education-specific immigration shocks ($d\tilde{I}$ and $d\tilde{I}_g$ in equation (3.5)) are held constant through the inclusion of general and education-specific time fixed effects ($\Delta\pi_t$ and $s_g \times \Delta\pi_t$ in equation (2.1)). If we replace the first differences in equation (2.2) by derivatives, the parameter θ^{skill} as estimated by the spatial skill cell approach is given by:

$$\theta^{skill} = \frac{(d \log w_{LI} - d \log w_{LE}) - (d \log w_{HI} - d \log w_{HE})}{(dI_{LI} - dI_{LE}) - (dI_{HI} - dI_{HE})}$$

From equation (3.5), it identifies the direct partial effect of immigration, holding the total and the education-specific immigration shock constant:

$$\theta^{skill} \cong \frac{d \log w_{ga}}{d I_{ga}} \Big|_{d \tilde{I}_g} = \frac{d \log w_{gI} - d \log w_{gE}}{d I_{gI} - d I_{gE}} = (\gamma - 1)$$

It is unambiguously negative (as $\gamma < 1$), the more so the less substitutable experienced and inexperienced workers are within education groups.

3.2.2 Mixture Approach

Studies that exploits variation in the immigration shock across both skill-cells and regions (e.g., LaLonde and Topel, 1991, Card, 2009) identify the relative wage effect of immigration by education, as any effects of immigration common to all education groups are differenced out. The parameter $\theta^{spatial,skill}$ estimated by the mixture approach may thus be thought of as the direct partial effect of immigration holding the total immigration shock constant, and from equation (3.5) it identifies

$$\theta^{spatial,skill} \cong \frac{d \log w_g}{d \tilde{I}_g} \Big|_{d \tilde{I}} = \frac{d \log w_L - d \log w_H}{d \tilde{I}_L - d \tilde{I}_H} = (\beta - 1)$$

It is unambiguously negative (as $\beta < 1$), the more so the less substitutable low and high skilled workers are in production.

It should be noted that the education-specific immigration shocks in the expression above, $d \tilde{I}_L$ and $d \tilde{I}_H$, are measured in efficiency units (see equation 3.3), whereas they are measured in head counts in the empirical specification (see equation 2.4). While the two measures are highly correlated, they will not be the same if the efficiency of inexperienced and experienced in production differs.

The parameter $\theta^{spatial,skill}$ therefore corresponds to the inverse of the elasticity of substitution between low and high skilled workers ($\beta - 1$) only approximately.

3.2.3 Pure Spatial Approach

The pure spatial approach adopted by for example Altonji and Card (1991) identifies the total wage effect of immigration for workers in education and experience group ga . From equation (3.5), the parameter $\theta_{ga}^{spatial}$ identifies $\frac{\Delta \log w_{ga}}{dI}$, where $dI = \frac{N^{Im}}{N^N}$ denotes the total immigration shock in head counts:

$$\theta_{ga}^{spatial} \cong \frac{d \log w_{ga}}{dI} = \varphi \frac{d\bar{i}}{dI} + (\beta - 1) \left(\frac{d\bar{i}_g}{dI} - \frac{d\bar{i}}{dI} \right) + (\gamma - 1) \left(\frac{dI_{ga}}{dI} - \frac{d\bar{i}_g}{dI} \right) \quad (3.6)$$

This total effect measures not only the direct partial effect of an immigration induced labor supply shock on native workers in skill cell ga as in the national skill cell and mixture approach, but also the indirect effects through complementarities across skill cells and across capital and labor. See Dustmann et al. (2013) for a detailed derivation and structural interpretation of the parameter for the case where workers differ only by skills.

It should be noted that it is straightforward to transform total wage effects into relative wage effects by experience:

$$\frac{d \log w_{gI}}{dI} - \frac{d \log w_{gE}}{dI} = \frac{d \log w_{ga}}{dI_{ga}} \Big|_{d\bar{i}, d\bar{i}_g} \frac{dI_{gI} - dI_{gE}}{dI}$$

In contrast, since total wage effects contain additional information to the relative wage effects by experience, the latter cannot be transformed into the former.

3.3 Interpretation if Labor Supply is Elastic, but Constant Across Skill Groups

So far, we have discussed the interpretation of the relative and total wage effects of immigration under the assumption that native labor does not respond to wage changes. Next, we turn to the case in which native labor supply does adjust to wage changes, but the labor supply elasticity is constant across skill groups (i.e., $\eta_{ga} = \eta \forall g, a$). With elastic, but constant labor supply, the equilibrium wage response is determined by the intersections of the firm's demand curve (equation (3.2)), the education-experience specific, the education-specific, and the aggregate labor supply curves:

$$d\log L_{ga} = dI_{ga} + \eta d\log w_{ga}$$

$$d\log L_g = d\tilde{I}_g + \eta(s_{gI}d\log w_{gI} + s_{gE}d\log w_{gE}) = d\tilde{I}_g + \eta d\log w_g \text{ and}$$

$$d\log L = d\tilde{I} + \eta(s_L d\log w_L + s_H d\log w_H) = d\tilde{I} + \eta d\log w$$

The equilibrium wage response becomes

$$d\log w_{ga} = \frac{\varphi}{1-\varphi\eta} d\tilde{I} + \frac{(\beta-1)}{(1-\eta(\beta-1))} (d\tilde{I}_g - d\tilde{I}) + \frac{(\gamma-1)}{(1-\eta(\gamma-1))} (dI_{ga} - d\tilde{I}_g) \quad (3.8)$$

The native employment response follows straightforwardly from the native labor curve:

$$d\log L_{ga}^N = \eta d\log w_{ga} \quad (3.9)$$

Based on equation (3.8), it is straightforward to provide a structural interpretation of the relative and total effects of immigration identified by the three empirical approaches. With elastic labor supply, the relative wage effect by experience identified by the national skill cell approach does not only depend on the elasticity of substitution between experienced and inexperienced workers, but also on the labor supply elasticity:

$$\theta^{skill} \cong \frac{d\log w_{ga}}{dI_{ga}} \Big|_{d\tilde{I}, d\tilde{I}_g} = \frac{d\log w_{gI} - d\log w_{gE}}{dI_{gI} - dI_{gE}} = \frac{(\gamma-1)}{(1-\eta(\gamma-1))}$$

Similarly, the relative wage effect by education identified by the mixture approach depends both on the elasticity of substitution between low and high skilled workers and the elasticity of labor supply:

$$\theta^{spatial,skill} \cong \frac{dlogw_g}{d\tilde{I}_g} \Big|_{d\tilde{I}} = \frac{dlogw_L - dlogw_H}{d\tilde{I}_L - d\tilde{I}_H} = \frac{(\beta-1)}{(1-\eta(\beta-1))},$$

while the total wage effect identified by the spatial approach now depends on the underlying structural parameters as follows:

$$\begin{aligned} \theta_{ga}^{spatial} &\cong \frac{dlogw_{ga}}{dI} \\ &= \frac{\varphi}{1-\varphi\eta} \frac{d\tilde{I}}{dI} + \frac{(\beta-1)}{(1-\eta(\beta-1))} \left(\frac{d\tilde{I}_g}{dI} - \frac{d\tilde{I}}{dI} \right) + \frac{(\gamma-1)}{(1-\eta(\gamma-1))} \left(\frac{dI_{ga}}{dI} - \frac{d\tilde{I}_g}{dI} \right). \end{aligned}$$

The relative and total native employment effects identified by each empirical approach follow straightforwardly from equation (3.9). These expressions highlight that both the relative and total wage effects depend now on demand and supply parameters (elasticities of substitution and labor supply elasticities). They become more muted, whereas the respective employment effects amplify, as the labor supply elasticity increases. If native labor supply is infinitely elastic, the relative and total wage effects of immigration approach zero, whereas the respective employment effects approach -1, implying that each immigrant displaces one native worker. As discussed, the labor supply elasticity is likely to be larger at the national level than at the local level—which, as emphasized by Borjas (2003), may help to explain why the national skill cell approach tends to produce more negative wage effects than the mixture approach.

Since $dlogL_{ga}^N = \eta dlogw_{ga}$, and if wages are—as assumed here—fully flexible, an estimate of the native labor supply elasticity can be obtained by dividing the relative or total

employment effects of immigration by the respective native wage effect of immigration. For

example, $\eta = \frac{d \log L_{ga}^N / dI}{d \log w_{ga} / dI}$.

3.4 Interpretation if Labor Supply Elasticities Vary Across Skill Groups

So far, we have assumed that the elasticity of labor supply is constant across education-experience groups. It is likely however that labor supply elasticities differ between different groups of workers, both on national and local level (see our discussion above). Alternatively, the degree of wage rigidity may differ across groups of workers. Next, we highlight the implications of heterogeneity in labor supply elasticities or in the degree of wage rigidities across groups of workers for the interpretation of the relative and total effects of immigration.

3.4.1 The Mixture Approach

Consider first the mixture approach which recovers the wage effect of immigration by education.

Using CES aggregates as weights,

$$d \log w_g = s_{gI} d \log w_{gI} + s_{gE} d \log w_{gE},$$

and using equation (3.5), we can write the two education-specific labor demand curves as

$$d \log w_L = \varphi d \log L + (\beta - 1)(d \log L_L - d \log L)$$

$$d \log w_H = \varphi d \log L + (\beta - 1)(d \log L_H - d \log L)$$

The two education-specific labor supply curves equal

$$d \log L_L = d \tilde{I}_L + \eta_L d \log w_L$$

$$d \log L_H = d \tilde{I}_H + \eta_H d \log w_H.$$

By plugging the supply curves into the demand curves and solving the two equations for $d\log w_L$ and $d\log w_H$ we derive the relative wage effect by education, which corresponds to the estimated parameter as

$$\theta^{spatial,skill} \cong \frac{d\log w_L - d\log w_H}{d\tilde{I}_L - d\tilde{I}_H} = \frac{(\beta-1)(d\tilde{I}_L(1-\varphi\eta_H) - d\tilde{I}_H(1-\varphi\eta_L)) / (d\tilde{I}_L - d\tilde{I}_H)}{1 - (\beta-1)[\eta_L(1+s_L\phi) + \eta_H(1+s_H\phi) - \eta_L\eta_H\phi]} \quad (3.10)$$

where $\phi = \frac{\varphi}{\beta-1} - 1$. The empirically estimated relative native employment effect by education,

$\theta_{emp}^{spatial,skill}$, corresponds to (using $d\log L_g^N = \eta_g d\log w_g$)

$$\theta_{emp}^{spatial,skill} \cong \frac{d\log N_L^N - d\log N_H^N}{d\tilde{I}_L - d\tilde{I}_H} = \frac{(\beta-1)(\eta_L d\tilde{I}_L(1-\varphi\eta_H) - \eta_H d\tilde{I}_H(1-\varphi\eta_L)) / (d\tilde{I}_L - d\tilde{I}_H)}{1 - (\beta-1)[\eta_L(1+s_L\phi) + \eta_H(1+s_H\phi) - \eta_L\eta_H\phi]}$$

A key implication of the canonical model is that natives who suffer the largest inflow of immigrations (e.g., low-skilled workers if immigration is relatively low skilled) suffer the largest decline in wages as well as employment. With heterogeneous labor supply elasticities, however, this may no longer hold—a phenomenon we refer to as “perverse” effects (see also Dustmann, Schönberg, and Stuhler, 2016). Expression (3.10) illustrates the possibility of perverse effects. Suppose that immigration is predominantly low skilled (i.e., $d\tilde{I}_L > d\tilde{I}_H$), that capital is not fully elastic ($\varphi < 0$) and that some high skilled migrants enter the local labor market ($d\tilde{I}_H > 0$).² If the labor supply of low-skilled natives is very elastic relative to that of high skilled natives ($\eta_L > \eta_H$), the term $\frac{d\tilde{I}_L(1-\varphi\eta_H) - d\tilde{I}_H(1-\varphi\eta_L)}{d\tilde{I}_L - d\tilde{I}_H}$ in equation (3.10) can be negative, and low skilled wages *increase* relative to high skilled wages—as for low skilled workers, much of the labor market response to immigration will be absorbed in a decline in employment rather than in a decline in wages. In consequence, native low skilled employment will strongly decline relative to native high skilled

² Dustmann, Schönberg and Stuhler (2016) show that in the case of three education groups perverse wage effects may also arise if capital supply is fully elastic.

employment. The relative wage and employment effects of immigration by education may therefore be of opposite sign—which reinforces the need to analyze employment and wage responses to immigration jointly to obtain a complete picture of the labor market impacts of immigration.

3.4.2 The National Skill Cell Approach

Consider next the national skill cell approach which, in the case of inelastic or constant native labor supply, recovers the relative wage effect of immigration by experience within education groups. We now show that the parameter estimated by the national skill approach have no meaningful interpretation if labor supply elasticities vary across skill groups.

Recall that the equilibrium is determined by the demand for labor given by equation (3.2) and the supplies for labor given by equation (3.1). This leads to the following two equations:

$$d\log w_{LI} - d\log w_{LE} = (\gamma - 1)(dI_{LI} - dI_{LE} + \eta_{LI}d\log w_{LI} - \eta_{LE}d\log w_{LE})$$

$$d\log w_{HI} - d\log w_{HE} = (\gamma - 1)(dI_{HI} - dI_{HE} + \eta_{HI}d\log w_{HI} - \eta_{HE}d\log w_{HE})$$

These two equations show that the relative wage effects of one experience group versus the other can be different for low skilled workers than for high skilled workers; that is, $\frac{d\log w_{LI} - d\log w_{LE}}{dI_{LI} - dI_{LE}} \neq$

$\frac{d\log w_{HI} - d\log w_{HE}}{dI_{HI} - dI_{HE}}$. Such differential effects make the triple difference estimator θ^{skill} in equation

(2.2) difficult to interpret. To see this, consider the model counterpart of θ^{skill} (introduced in Section 3.2.1):

$$\begin{aligned} \theta^{skill} &\hat{=} \frac{(d\log w_{LI} - d\log w_{LE}) - (d\log w_{HI} - d\log w_{HE})}{(dI_{LI} - dI_{LE}) - (dI_{HI} - dI_{HE})} \\ &= \frac{\frac{d\log w_{LI} - d\log w_{LE}}{dI_{LI} - dI_{LE}}(dI_{LI} - dI_{LE}) - \frac{d\log w_{HI} - d\log w_{HE}}{dI_{HI} - dI_{HE}}(dI_{HI} - dI_{HE})}{(dI_{LI} - dI_{LE}) - (dI_{HI} - dI_{HE})} \end{aligned}$$

Since $\frac{d\log w_{LI} - d\log w_{LE}}{dI_{LI} - dI_{LE}} \neq \frac{d\log w_{HI} - d\log w_{HE}}{dI_{HI} - dI_{HE}}$, it cannot be factored out. In consequence, the relative wage effect by experience for one education group receives a weight larger than 1, whereas it receives a negative weight for the other education group. For the immigration shocks observed in the 2000 US Census, $\frac{dI_{LI} - dI_{LE}}{(dI_{LI} - dI_{LE}) - (dI_{HI} - dI_{HE})} = 2.34$, and $-\frac{dI_{HI} - dI_{HE}}{(dI_{LI} - dI_{LE}) - (dI_{HI} - dI_{HE})} = -1.34$.³ The triple differencing estimator therefore does not present a meaningful weighted average of the relative wage effects by experience for each education group.

Estimates of θ^{skill} remain interpretable, addressing the question how immigration affects wages of inexperienced workers relative to experienced workers in the same education group, in the special case in which the education-experience specific immigration shocks are the same for inexperienced and experienced workers within one of the two education groups. For example, if $dI_{HI} - dI_{HE} = 0$, θ^{skill} reduces to $\frac{d\log w_{LI} - d\log w_{LE}}{dI_{LI} - dI_{LE}}$. In the general case, however, $dI_{LI} \neq dI_{LE}$ and $dI_{HI} \neq dI_{HE}$, and the difference-in-difference approach becomes “fuzzy”—which, as discussed in Chaisemartin and D'Haultfoeuille (2015), makes estimates in the presence of treatment effect heterogeneity difficult to interpret.

3.4.3 The Pure Spatial Approach

Consider finally the pure spatial approach. The equilibrium wage and native employment response to immigration are determined by the demand for labor given by equation (3.2) and the supplies

³ In the 2000 US Census, the education-experience specific immigration shocks, computed as the number of immigrants in each skill group who entered the US in the last two years divided by the total number of residents (natives + previous immigrants) in that skill group, equal $dI_{UI} = 0.0225$, $dI_{UE} = 0.0073$, $dI_{SI} = 0.0113$, and $dI_{SE} = 0.0026$. Low and high skilled workers are defined as those with high school degree or less and those with at least some college, and inexperienced and experienced workers are defined as having up to 20 or more than 20 years of potential experience (age – 6 – years of schooling).

for labor given by equation (3.1). The total wage and employment effects of immigration estimated by the spatial approach simply follow from $\frac{d \log w_{ga}}{dI}$ and $\frac{d \log L_{ga}^N}{dI}$. With heterogeneous labor supply elasticities, it is difficult to obtain intuitive analytical expressions for the total effects. Nevertheless, they remain meaningful and policy-relevant parameters even in the presence of heterogeneous labor supply elasticities, addressing the same question as in the case of homogenous (or inelastic) labor supply responses: “How does the overall immigration shock affect wages and employment of a particular native education-experience group?” Under the assumption that wages are fully flexible, estimates for the education-experience specific labor supply elasticities can then be obtained by dividing the estimates for the total wage effect of a particular education-experience group by the respective estimate of the total employment effect; that is, $\eta_{ga} = \frac{d \log L_{ga}^N / dI}{d \log w_{ga} / dI}$.

4. Downgrading and Misclassification

4.1 Empirical Evidence for Downgrading: A Simple Imputation Procedure

“Downgrading” occurs when the position of immigrants in the labor market, which is typically measured by wage or occupation, is systematically lower than the position of natives with the same observed education and experience levels. Downgrading means that immigrants receive lower returns to the same measured skills than natives when these skills are acquired in their country of origin. Immigrants who are observed to be high skilled or experienced may thus work in low skilled or inexperienced jobs, and therefore compete with low skilled and inexperienced natives.

Next, we propose a simple procedure to impute the *effective* education-experience distribution of immigrants.⁴ The imputation procedure proposed here uses (i) both occupational and wage data to

⁴ Imputations of effective skill measures have previously been considered by Borjas (2003), who imputes the effective experience of immigrant workers based on their wage. Similarly, Dustmann and Frattini (2014) impute the

identify the skill of immigrant workers, and (ii) imputes both the effective education and effective experience of immigrant workers.

First, define the *type* of a native worker as the interaction between G education and A experience groups, as to distinguish between GxA types e_1, \dots, e_{GxA} . Whereas for native workers their observed type is equal to their effective type, the type \tilde{e}_i reported for immigrant workers may misclassify them with respect to the native type distribution e_i (i.e. $\tilde{e}_i \neq e_i$). Second, define the *job* of a worker as the interaction between O occupations and W wage centiles, as to distinguish OxW jobs s_1, \dots, s_{OxW} . We assume that immigrant and native workers of the same *effective* education-experience type are perfect substitutes in production and equally likely to work in a particular job.

Let $P(s_i = k | e_i = j)$ denote the conditional probability that a worker of effective education-experience type $e_i = j$ works in job $s_i = k$. Due to the misclassification of immigrant workers, it is observed only for native workers. For immigrant workers, we instead observe the conditional probability that the immigrant worker of *observed* education-experience type $\tilde{e}_i = l$ works in job $s_i = k$, $P^I(s_i = k | \tilde{e}_i = l)$. The conditional probability that an immigrant worker of observed type $\tilde{e}_i = l$ is effectively of type $e_i = j$ is $P^I(e_i = j | \tilde{e}_i = l)$. This probability captures the misclassification of immigrant workers to education-experience groups.

The conditional probability that an immigrant worker of observed type $\tilde{e}_i = l$ has the skill $s_i = k$ can thus be written as

$$P^I(s_i = k | \tilde{e}_i = l) = \sum_{j=1}^{GxA} P(s_i = k | e_i = j) P^I(e_i = j | \tilde{e}_i = l). \quad (4.1)$$

effective education of immigrants as the average education of natives in the same occupation, and Docquier, Ozden and Peri (2014) impute the share of college-educated immigrants based on 1-digit occupational categories.

The probabilities on the left-hand side ($P^l(s_i = k|\tilde{e}_i = l)$) and the first term in the sum on the right-hand side ($P(s_i = k|e_i = j)$) can be directly estimated from the data. The second term in the sum on the right-hand side ($P^l(e_i = j|\tilde{e}_i = l)$) is our object of interest and not directly observed in the data.

We stack equation (4.1) across all OxW jobs (occupation-wage groups) to obtain

$$\mathbf{p}_l^l = \sum_{j=1}^{GxA} \mathbf{p}_j \phi_{j,l}, \quad (4.2)$$

The resulting vector \mathbf{p}_l^l of length OxW on the left-hand side represents the job distribution of immigrant workers of observed type $\tilde{e}_i = l$, while the vectors $\mathbf{p}_1, \dots, \mathbf{p}_{GxA}$, also of length OxW , represent the job distribution for natives of education-experience type $e_i = j$. The scalar $\phi_{j,l} = P^l(e_i = j|\tilde{e}_i = l)$ captures the probability that an immigrant worker of observed type l is effectively of type j , with $\phi_{j,l} > 0$ and $\sum_{j=1}^{GxA} \phi_{j,l} = 1 \forall l$.

Equation (4.2) implies the set of moment conditions $\mathbf{p}_l^l - \sum_{j=1}^{GxA} \mathbf{p}_j \phi_{j,l} = \mathbf{0}$. With a detailed categorization of jobs the number of moment conditions is larger than the number of unknown parameters, and the parameter vector $\boldsymbol{\phi}_l = (\phi_{1,l}, \dots, \phi_{GxA,l})$ can be estimated by the generalized methods of moments. Specifically, we replace the theoretical probability distributions \mathbf{p}_l^l and \mathbf{p}_j with the relative frequency distributions \mathbf{f}_l^l and \mathbf{f}_j as observed in the sample, and choose $\boldsymbol{\phi}_l$, subject to the constraints $\phi_{j,l} > 0$ and $\sum_{j=1}^{GxA} \phi_{j,l} = 1 \forall l$, such as to minimize

$$Q_l = \hat{\mathbf{m}}(\boldsymbol{\phi}_l)' \mathbf{W}_l \hat{\mathbf{m}}(\boldsymbol{\phi}_l), \quad (4.3)$$

where $\hat{\mathbf{m}}(\boldsymbol{\phi}_l) = \mathbf{f}_l^l - \sum_{j=1}^{GxA} \mathbf{f}_j \phi_{j,l}$, and $\mathbf{W}_l = \mathbf{I}$ as the positive definite weighting matrix.

We first implement this imputation procedure for immigrants that arrived within the previous two years in the 2003 to 2005 waves of the UK Labor Force Survey, distinguishing between two education groups (low and high skilled) and two experience groups (inexperienced

and experienced) to classify workers into four types. We consider 26 (2-digit) occupational categories and 10 wage deciles to distinguish between 260 jobs. We estimate, separately for each observed immigrant type l , the probability that the immigrant is effectively low skilled and inexperienced ($\phi_{LI,l}$), low skilled and experienced ($\phi_{LE,l}$), high skilled and inexperienced ($\phi_{HI,l}$) and high skilled and experienced ($\phi_{HE,l}$). We report the estimated probabilities in Table A.1. Unsurprisingly, among immigrant workers observed to be low skilled and inexperienced, nearly all immigrants are effectively low skilled and inexperienced (i.e., $\phi_{LI,LI} \approx 1$). Contrast this with immigrant workers observed to be high skilled and experienced. In this group, only 28% are effectively high skilled and experienced, while 58% are effectively low skilled and experienced (i.e., $\phi_{HE,HE} = 0.2$ and $\phi_{LE,HE} = 0.5$).

With estimates of $\phi_{j,l}$ in hand, it is straightforward to impute the effective education-experience distribution for immigrant workers according to $P^l(e_i = j) = \sum_{l=1}^{G \times A} P^l(\tilde{e}_i = l)\phi_{j,l}$. We report the effective distribution for immigrants who arrived to the UK between 2003 and 2005 in Panel B of Table A.2 (see also Table 2 in the main manuscript). We then repeat the exercise for the US and Germany, contrasting the observed and effective education-experience distribution of immigrant workers in Panels A and C. In all three countries, there is considerable downgrading by experience: in the United States and Germany, the share of immigrants who are observed to be experienced is more than twice as high as the share of immigrants who are effectively experienced. Downgrading by education is particularly striking in the United Kingdom: Whereas 69.7 % of immigrant arrivals to the UK would be classified as high skilled based on their reported education, only 24.6% are effectively high skilled, suggesting that far from a supply shock for high skilled workers, immigrant arrivals to the UK were a supply shock in the market for low skilled workers.

The conditional probabilities reported in Table A.1 do not impose any constraints on the probabilities that an immigrant worker observed to be of type l is effectively of type j . That is, they allow in principle for the possibility that an immigrant worker observed to be low skilled or inexperienced is employed in a high skilled or experienced job. They further allow the degree of downgrading by experience to be different for low and high skilled immigrant workers, and the degree of downgrading by education to be different for inexperienced and experienced immigrant workers.

To derive the likely bias from downgrading in the simplest way possible, we next assume that no immigrant upgrades, that the degree of downgrading by experience (denoted by ϕ_E) is the same for low and high skilled immigrant workers, and that the degree of downgrading by education (denoted by ϕ_S) is the same for inexperienced and experienced immigrant workers. These assumptions imply the following restrictions on the conditional probabilities:

- (i) $\phi_{LI,LI} = 1$ (and thus $\phi_{LE,LI} = \phi_{HI,LI} = \phi_{HE,LI} = 0$)
- (ii) $\phi_{LI,LE} = \phi_E, \phi_{LE,LE} = (1 - \phi_E)$ (and thus $\phi_{HI,LE} = \phi_{HE,LE} = 0$)
- (iii) $\phi_{LI,HI} = \phi_S, \phi_{HI,HI} = (1 - \phi_S)$ (and thus $\phi_{LE,HI} = \phi_{HE,HI} = 0$)
- (iv) $\phi_{LI,HE} = \phi_E \phi_S, \phi_{LE,HE} = (1 - \phi_E) \phi_S, \phi_{HI,HE} = \phi_E (1 - \phi_S), \phi_{HE,HE} = (1 - \phi_E)(1 - \phi_S)$

Table A.3 illustrates the relationship between the observed and the true (or effective) number of immigrants in each education-experience group under these restrictions. Consider for instance incoming immigrants observed to be skilled and inexperienced. Table A.3 shows that only a fraction of $(1 - \phi_S)$ work in skilled inexperienced jobs, while a fraction of ϕ_S downgrades to low skilled inexperienced jobs. Even though only ϕ_{LI}^0 unskilled and inexperienced immigrants are observed entering, $\phi_{LI}^0 + \phi_E \phi_S \phi_{LI}^0 + \phi_S \phi_{HI}^0 + \phi_E \phi_S \phi_{HE}^0$ are working in low skilled inexperienced

jobs. To obtain plausible estimates for the degrees of downgrading by experience and education, we estimate the constrained conditional probabilities for each of our three countries, and report them in Table A.4. The degree of downgrading in experience ϕ_E is large in all three countries (e.g., 0.54 in the US Census), while downgrading in education is large in the UK and Germany, but at 0.09 comparatively small in the US.

4.2 Interpretation of Relative and Total Effects of Immigration when Immigrants Downgrade

Downgrading may seriously bias the assessment of the wage and employment effects of immigration in the national skill-cell and in the mixture approach that rely on the pre-assignment of immigrants to education and experience cells and then exploit variation in the relative density of immigrants across those skill groups.

4.2.1 The Mixture Approach

Consider first the mixture approach. Assuming for simplicity that native labor supply is inelastic, that the true immigration shock in efficiency units equals the true immigration shock in head counts (i.e., $dI_g^{true} = dI_g^{true}$) and that region B is unaffected by immigration (i.e., $\Delta p_{LB} - \Delta p_{HB} = 0$ in equation 2.4), $\theta^{spatial,skill}$ recovers in the presence of downgrading:

$$\theta^{spatial,skill} \cong (\beta - 1) \frac{dI_L^{true} - dI_H^{true}}{dI_L^{o\ s} - dI_H^{o\ s}}$$

Downgrading therefore biases the relative wage effect of immigration by education by a factor of

$\frac{dI_L^{t\ ue} - dI_H^{t\ ue}}{dI_L^{obs} - dI_H^{obs}}$. If immigrants observed to be high skilled downgrade to low skilled jobs, $dI_U^{true} >$

$dI_U^{o\ s}$, and $dI_S^{true} < dI_S^{o\ s}$. Therefore, downgrading leads to an overestimate of the (negative)

direct partial effect of education if immigration is relatively unskilled (i.e., $dI_Y^o{}^s > dI_S^o{}^s$) and to an underestimate if immigration is relatively skilled (i.e., $dI_Y^o{}^s < dI_S^o{}^s$). In the US context, this type of bias is likely to be small, since downgrading by education is small (see Table A.4, $\hat{\phi}_s = 0.0$), in contrast to downgrading by experience.

4.2.2 The National Skill Cell Approach

Consider next the relative wage effect by experience as estimated by Borjas (2003). Assuming for simplicity that native labor supply is inelastic, and allowing for downgrading, the triple difference estimator in equation (2.2) recovers

$$\theta^{skill} \cong (\gamma - 1) \frac{(dI_{LI}^{t\ ue} - dI_{LE}^{t\ ue}) - (dI_{HI}^{t\ ue} - dI_{HE}^{t\ ue})}{(dI_{LI}^{obs} - dI_{LE}^{obs}) - (dI_{HI}^{obs} - dI_{HE}^{obs})} \quad (4.4)$$

Thus, downgrading leads to a biased estimate of the relative wage effect by experience by the factor $\frac{(dI_{LI}^{t\ ue} - dI_{LE}^{t\ ue}) - (dI_{HI}^{t\ ue} - dI_{HE}^{t\ ue})}{(dI_{LI}^{obs} - dI_{LE}^{obs}) - (dI_{HI}^{obs} - dI_{HE}^{obs})}$. In general, this bias factor may be smaller or larger than 1 so that both underestimation and overestimation of the relative wage effect is possible. However, if the denominator in equation (4.4) is positive – which is for instance the case when the observed education-experience specific immigration shocks are computed from the 2000 US Census based on immigrants who entered the country in the past two years – then the bias factor exceeds 1, and downgrading leads to an overestimate of the (negative) relative wage effect by experience. We illustrate this in Figure A.1 where we plot the bias factor against the degree of downgrading by education, assuming three different degrees of downgrading by experience (0, 0.3, and 0.6). Specifically, we take the number of residents (natives and immigrants residing in the country for more than two years) and the number of immigrants who entered the US in the past two years to compute resident employment and baseline and the observed education-experience specific

immigration shocks.⁵ For each degree of downgrading by skill and by experience (for immigrants entering the country), we then compute the true education-experience specific immigration shocks as follows

$$dI_{LI}^{true} = (I_{LI}^o{}^s + \phi_E I_{LE}^o{}^s + \phi_S I_{HI}^o{}^s + \phi_S \phi_E I_{HE}^o{}^s) / L_{LI}^N \quad (4.5a)$$

$$dI_{LE}^{true} = ((1 - \phi_E) I_{LE}^o{}^s + (1 - \phi_E) \phi_S I_{HE}^o{}^s) / L_{LE}^N \quad (4.5b)$$

$$dI_{HI}^{true} = ((1 - \phi_S) I_{HI}^o{}^s + (1 - \phi_S) \phi_E I_{HE}^o{}^s) / L_{HI}^N \quad (4.5c)$$

$$dI_{HE}^{true} = I_{HE}^o{}^s (1 - \phi_S) (1 - \phi_E) / L_{HE}^N \quad (4.5d)$$

With the observed and the true education-experience immigration shocks in hand, it is then straightforward to compute the bias factor. When the degree of downgrading is large, but roughly compatible with UK data for the mid-2000s (e.g., $\phi_S = 0.4$ and $\phi_E = 0.6$), the relative wage effect by experience is overestimated by a factor of nearly 4). For degrees of downgrading roughly consistent with US data in the year 2000 (i.e., $\phi_S = 0.0$ and $\phi_E = 0.54$ from Table A.4), the bias factor is more than 2. That is, the estimated relative wage effect by experience is about twice as negative as the “true” relative wage effect that one would obtain if one could correctly allocate immigrants to education-experience cells. Since in the US context downgrading by experience exceeds downgrading by education, the bias from downgrading will be larger in the skill cell than in the mixture approach. Downgrading therefore provides an alternative explanation as to why the

⁵ From the US 2000 Census, education-experience specific employment at baseline equals $L_{LI}^N = 35,226 + 145,000$, $L_{LE}^N = 70,267 + 13,000$, $L_{HI}^N = 14,600 + 14,600$ and $L_{HE}^N = 116,350 + 116,350$, where low and high skilled workers are defined as those with high school degree or less and those with at least some college, and inexperienced and experienced workers are defined as having up to 20 or more than 20 years of potential experience (age – 6 – years of schooling), respectively. The observed number of immigrants who entered the US over the past two years in each education-experience groups equals $dL_{LI}^{lm} = I_{LI}^o{}^s = 24,277$, $dL_{LE}^{lm} = I_{LE}^o{}^s = 7,300$; $dL_{HI}^{lm} = I_{HI}^o{}^s = 1,530$ and $dL_{HE}^{lm} = I_{HE}^o{}^s = 3,411$. The education-experience specific immigration shocks therefore equal $dI_{LI}^o{}^s = 0.0225$, $dI_{LE}^o{}^s = 0.0073$, $dI_{HI}^o{}^s = 0.0113$, and $dI_{HE}^o{}^s = 0.0026$.

national skill cell approach typically produces more negative wages effects of immigration than the mixture approach.

4.2.3 The Pure Spatial Approach

In contrast, the total effects of immigration obtained from the pure spatial approach is robust to the downgrading of immigrants and remains a policy relevant parameter, addressing the question of how the overall immigration shock affects wages and employment of a particular skill group. As noted by Dustmann, Frattini and Preston (2013), in the spatial approach the actual position of immigrants in the distribution of native skills is part of the estimated parameter.

5. Structural Models and Substitutability between Immigrants and Natives

The papers we have discussed so far directly estimate the partial or total wage and employment effects of migration. More recently, an alternative literature has developed that – based on the canonical model – uses the model’s structure to calibrate the partial and total impacts of immigration on wages of native workers, based on estimates of the underlying structural parameters.⁶ The assumptions imposed on the data are thus far more stringent than those imposed by the empirical literature discussed so far, as one needs to assume that the chosen model structure is indeed correct.

Two prominent examples of this approach are Ottaviano and Peri (2012) and Manacorda, Manning and Wadsworth (2012).⁷ Both studies impose a production technology similar to the one described in Section 3.1, but allow immigrants and natives to be imperfect substitutes within each education-experience cell. Specifically, they introduce a third nest into the production technology:

⁶ This requires assumptions not only on the production technology, but also on the labor supply elasticity. Ottaviano and Peri (2012) and Manacorda, Manning and Wadsworth (2012) assume that labor supply is inelastic. Lull (2013) and Piyomdee (2015) relax this assumption and carefully model labor supply choices.

⁷ See Borjas, Freeman and Katz (1997) for an early application of this approach.

$L_{ga} = [\theta_{ga}^N L_{ga}^{N\delta} + \theta_{ga}^I L_{ga}^{I\delta}]^{1/\delta}$, and where $1/(1-\delta)$ is the elasticity of substitution between natives and immigrants workers within an education-experience group. With the third nest in the production function, the firm's demand curve for skill cell ga and type j (immigrant versus native) becomes (see e.g., Ottaviano and Peri, 2012):

$$\begin{aligned} d\log w_{ga}^j &= \varphi d\log L + (\beta - 1)(d\log L_g - d\log L) + (\gamma - 1)(d\log L_{ga} - d\log L_g) \\ &+ (\delta - 1)(d\log L_{ga}^j - d\log L_{ga}) \end{aligned} \quad (5.1)$$

for $j = N, Im$. Assuming for simplicity that native employment does not adjust to immigration if native labor supply is inelastic, the wage change for resident immigrants in an education-experience group relative to the wage change for natives in that same group in response to immigration equals

$$d\log w_{ga}^{Im} - d\log w_{ga}^N = (\delta - 1)(d\log L_{ga}^I - d\log L_{ga}^N) = (\delta - 1)dI_{ga}^{Im} \quad (5.2)$$

where dI_{ga}^{Im} is the shock *resident* immigrants in the education-experience group ga face.⁸ Thus, if within an education-experience group immigrants and natives are imperfect substitutes (i.e., $\delta < 1$), wages of existing immigrants will decline relative to wages of natives in the same education-experience group.

Equations (5.1) and (5.2) illustrate the key role that the elasticity of substitution between immigrants and natives within the same skill cell plays in the structural approach. If immigrants and natives are imperfect substitutes within education-experience groups, and mostly low-skilled inexperienced immigrants enter the labor market, then the incumbent low-skilled inexperienced immigrants will bear most of the burden of increased immigration—the more so the less

⁸ That is, $dI_{ga}^{Im} = dL_{ga}^{Im}/L_{ga}^{Im}$, where dL_{ga}^{Im} is the inflow of immigrant workers into education-experience cell ga , and L_{ga}^{Im} the number of resident immigrants in that cell.

substitutable immigrants and natives are within skill cells. In contrast, wages of not only high skilled experienced natives, but also of low skilled inexperienced natives may increase in response to immigration if immigrants and natives are not very substitutable within education-experience groups.

Ottaviano and Peri (2012) and Manacorda, Manning and Wadsworth (2012) estimate the elasticity of substitution between immigrants and natives, by relating the relative wage changes of immigrants and natives observed in a particular skill cell to the respective relative employment changes—as implied by equation (5.2). Both studies find that immigrants and natives are imperfect substitutes and report estimates for the elasticity of about 20 (Ottaviano and Peri 2012) and 7 (Manacorda, Manning and Wadsworth 2012). But these estimates for the elasticity of substitution between immigrants and natives may be impaired by the downgrading of immigrants.⁹ The elasticity of substitution between immigrants and natives $1/(1-\delta)$ is a production technology parameter which refers to immigrants and natives who are *identical* in education and experience. However, with downgrading, this assumption is violated since immigrants and natives are now grouped into the same education-experience cell based on their *observed* education and experience, even though – from a production point of view – they are *not* identical in those two skills if there is downgrading. This will cause a bias in the estimates of the elasticity of substitution between the two. Consider for instance existing immigrants who are *observed* to be high skilled and experienced. Further, assume that immigrants and natives who *work* in the same education-experience group are perfect substitutes. Wage changes in response to immigration of existing immigrants observed to be high skilled and experienced will then be equal to a weighted average

⁹ See also Dustmann and Preston (2012) who make this point formally in a more dynamic setting with only one skill dimension (education), and where immigrants upgrade after initially downgrading upon arrival.

of wage changes of low skilled inexperienced natives, low skilled experienced natives, high skilled inexperienced natives and low skilled experienced natives, where the weights depend on the degrees of downgrading (i.e., $\phi_S \phi_E$, $\phi_S(1 - \phi_E)$, $\phi_E(1 - \phi_S)$ and $(1 - \phi_S)(1 - \phi_E)$). Therefore, if immigration (as observed in the US data) is predominantly low skilled and inexperienced, wage changes of immigrants *observed* to be high skilled and experienced will be smaller than of natives in that group (since $d\log w_{HE} > d\log w_{LI}$). In consequence, due to downgrading, immigrants and natives may appear to be imperfect substitutes even though, if correctly classified, they are not.

We illustrate this in Figure A.2, where we plot $\frac{d\log w_{SEObs}^I - d\log w_{SE}^N}{dI_{SEObs}^I}$, which from equation (5.2) identifies $(\delta - 1)$, against the degree of downgrading by education, separately for three possible values for the degree of downgrading by experience (0, 0.3, and 0.6). Specifically, we first compute – based on the number of natives, residing and entering immigrants observed in each education-experience cell in the 2000 US Census – the true immigration shocks in each education-experience cell, for varying degrees of downgrading, according to equations (4.5a) to (4.5d). For these true immigration shocks, we then compute the implied wage changes for natives using equation (3.5). We further calculate the wage change for immigrants observed to be high skilled and experienced according to:

$$\begin{aligned} d\log w_{SEObs}^{Im} = & \phi_E \phi_S d\log w_{UI}^N + \phi_S (1 - \phi_E) d\log w_{UE}^N + \phi_E (1 - \phi_S) d\log w_{SI}^N \\ & + (1 - \phi_E)(1 - \phi_S) d\log w_{SE}^N \end{aligned}$$

The figure demonstrates that the estimate for $(\delta - 1)$ becomes increasingly negative, and the inferred elasticity of substitution between immigrants and natives ($1/(1 - \delta)$) therefore becomes smaller, as the degree of downgrading increases. For example, for degrees of downgrading roughly consistent with US data (i.e., $\phi_S = 0.1$ and $\phi_E = 0.54$), the estimate for $(\delta - 1)$ roughly equals

-0.08, corresponding to an elasticity of substitution between immigrants and natives of 12.5 (compared to an estimate of 20 in Ottaviano and Peri, 2012), although the “true” elasticity is infinity.

If the estimates for the degree of substitutability between immigrants and natives are biased, then this will cause the estimates of the total effects of immigration as predicted by the structure of the model to be biased—even if the model is otherwise correctly specified. Importantly, incorrectly assuming that immigrants and natives are imperfect substitutes within education-experience groups will understate wage losses for natives most exposed to immigration (i.e., low skilled inexperienced natives in the US), overstate possible wage gains for natives least exposed to immigration (high skilled experienced natives), and overstate the wage losses of existing immigrants. Therefore, based on the observed immigration shocks in the US context, downgrading is likely to lead to an overstatement of the negative (relative) wage responses of natives in the mixture and in particular the skill cell approach, but an understatement of the (total) wage responses of natives in the structural approach.

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Table A.1: The Effective Skill of Immigrant Arrivals in the UK LFS, 2003-2005

(a) Low education, 1-20 yrs experience

| <u>Imputed skill:</u> | <u>Potential Experience</u> | |
|-----------------------|-----------------------------|-----------|
| | Education 1-20 yrs | 21-40 yrs |
| low | 99% | 0% |
| high | 0% | 1% |

(b) Low education, 21-40 yrs experience

| <u>Imputed weights:</u> | <u>Potential Experience</u> | |
|-------------------------|-----------------------------|-----------|
| | Education 1-20 yrs | 21-40 yrs |
| low | 98% | 1% |
| high | 0% | 1% |

(c) High education, 1-20 yrs experience

| <u>Imputed weights:</u> | <u>Potential Experience</u> | |
|-------------------------|-----------------------------|-----------|
| | Education 1-20 yrs | 21-40 yrs |
| low | 66% | 0% |
| high | 33% | 1% |

(d) High education, 21-40 yrs experience

| <u>Imputed weights:</u> | <u>Potential Experience</u> | |
|-------------------------|-----------------------------|-----------|
| | Education 1-20 yrs | 21-40 yrs |
| low | 0% | 58% |
| high | 14% | 28% |

Note: The table reports the effective skill of immigrant arrivals, as estimated from the distribution of workers across wage centiles and 2-digit occupations. The low education group contains workers who completed fulltime education at age 18 or less. Potential experience is computed as age minus the age at which fulltime education was completed. Immigrant arrivals are workers who have arrived within the last two years. See Appendix 4.1 for details on the imputation procedure. Source: UK LFS, years 2003-2005.

Table A.2: The Observed and Effective Skills of Immigrant Arrivals

(a) United States (Census, year 2000)

Observed Potential Experience

| Education | 1-20 yrs | 21-40 yrs | total |
|-----------|----------|-----------|-------|
| low | 44.1% | 13.4% | 57.6% |
| high | 36.3% | 6.2% | 42.5% |
| total | 80.4% | 19.6% | |

Effective Potential Experience

| Education | 1-20 yrs | 21-40 yrs | total |
|-----------|----------|-----------|-------|
| low | 56.2% | 4.0% | 60.3% |
| high | 34.1% | 5.6% | 39.7% |
| total | 90.3% | 9.7% | |

(b) United Kingdom (UK LFS, years 2003-2005)

Observed Potential Experience

| Education | 1-20 yrs | 21-40 yrs | total |
|-----------|----------|-----------|-------|
| low | 24.1% | 6.2% | 30.3% |
| high | 62.7% | 7.0% | 69.7% |
| total | 86.8% | 13.2% | |

Effective Potential Experience

| Education | 1-20 yrs | 21-40 yrs | total |
|-----------|----------|-----------|-------|
| low | 71.3% | 4.1% | 75.4% |
| high | 21.7% | 2.9% | 24.6% |
| total | 93.0% | 7.0% | |

(c) Germany (IABS, year 2000)

Observed Potential Experience

| Education | 1-20 yrs | 21-40 yrs | total |
|-----------|----------|-----------|-------|
| low | 36.3% | 6.2% | 42.5% |
| high | 51.4% | 6.1% | 57.5% |
| total | 87.7% | 12.3% | |

Effective Potential Experience

| Education | 1-20 yrs | 21-40 yrs | total |
|-----------|----------|-----------|-------|
| low | 61.9% | 0.0% | 61.9% |
| high | 35.8% | 2.3% | 38.1% |
| total | 97.7% | 2.3% | |

Note: The table reports the observed and imputed effective skills of immigrants who arrived within the last two years. The imputation of effective skills is based on the distribution of workers across wage centiles and 2-digit occupations, as described in Section 4.1 of the appendix. Source: US Census 2000, UK LFS 2003-2005, and IABS 2000.

Table A.3: The Relationship between the Observed and True Number of Immigrants in Each Education-Experience Group when Immigrants Downgrade

| | | <u>true</u> | | | |
|-----------------|----------------------------|------------------------------|------------------------------------|------------------------------------|--|
| | | low skilled inexperienced | low skilled experienced | high skilled inexperienced | high skilled experienced |
| <u>observed</u> | low skilled inexperienced | I_{LI}^{obs} | 0 | 0 | 0 |
| | low skilled experienced | $\phi_E I_{LE}^{obs}$ | $(1 - \phi_E) I_{LE}^{obs}$ | 0 | 0 |
| | high skilled inexperienced | $\phi_S I_{HI}^{obs}$ | 0 | $(1 - \phi_S) I_{HI}^{obs}$ | 0 |
| | high skilled experienced | $\phi_S \phi_E I_{HE}^{obs}$ | $\phi_S (1 - \phi_E) I_{HE}^{obs}$ | $(1 - \phi_S) \phi_E I_{HE}^{obs}$ | $(1 - \phi_S) (1 - \phi_E) I_{HE}^{obs}$ |

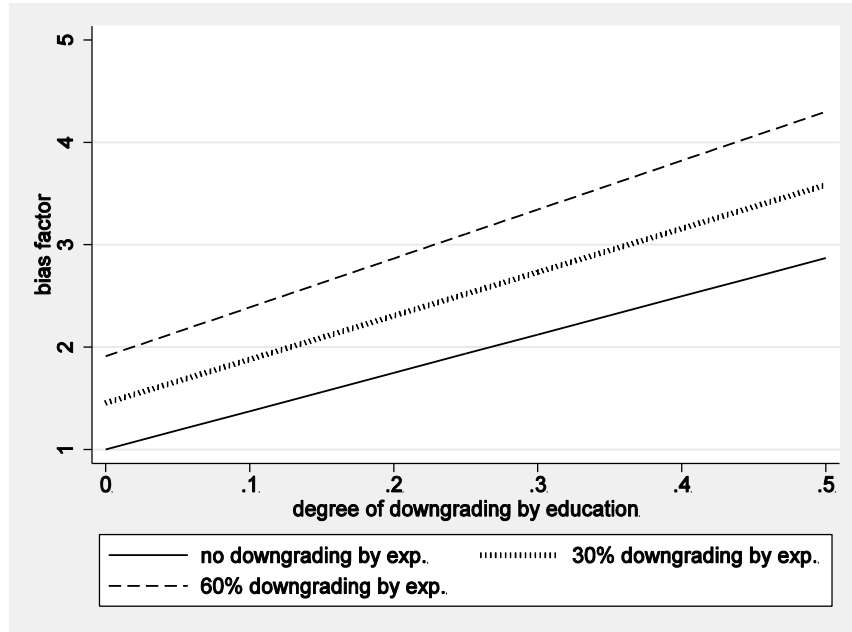
Note: The table illustrates the relationship between the observed and true number of immigrants in each education-experience group, where ϕ_S denotes the degree of downgrading by education and ϕ_E denotes the degree of downgrading by experience.

Table A.4: Immigrant Downgrading with Constrained Weights

| | Downgrading | |
|--|--------------|---------------|
| | in education | in experience |
| United States <i>US Census, 2000</i> | 0.09 | 0.54 |
| United Kingdom <i>UK LFS, 2003-2005</i> | 0.42 | 0.57 |
| Germany <i>IABS, 2000</i> | 0.44 | 0.99 |

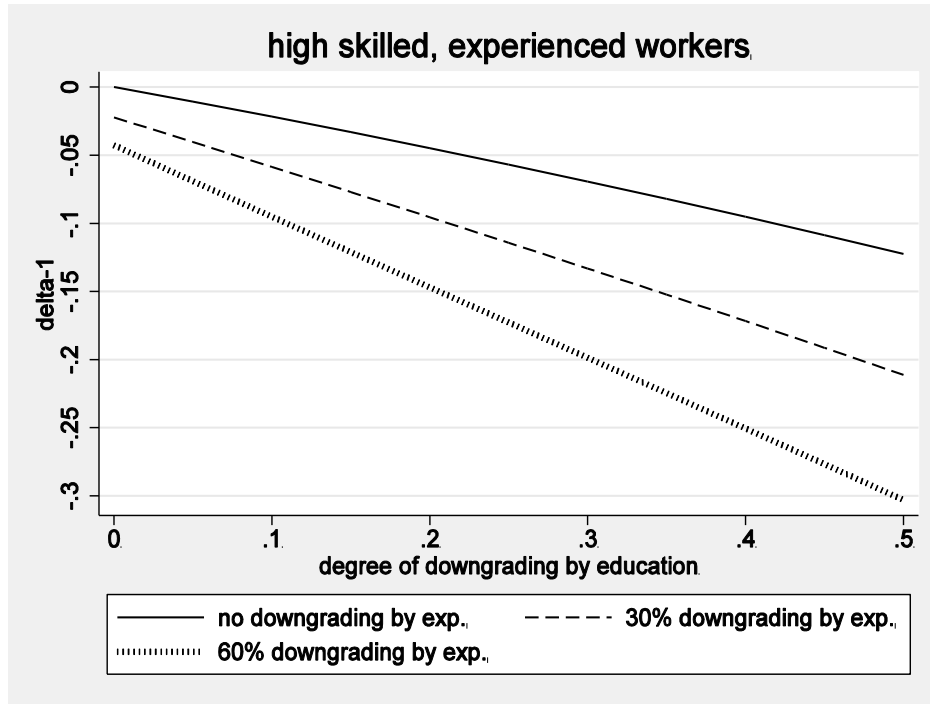
Note: The table reports the degree of downgrading in education and experience of immigrant arrivals who arrived within the last two years, as estimated from the distribution of workers across wage centiles and 2-digit occupations. See Appendix 4.1 for details on the imputation procedure.

Figure A.1: Illustration of the Bias in the National Skill Cell Approach when Immigrants Downgrade



Note: The figure illustrates the bias which may arise in estimates of the relative wage effect by experience of immigration obtained by the national skill cell approach when immigrants downgrade. The figure plots the bias factor against the degree of downgrading by education, for three degrees of downgrading by experience (0, 0.3 and 0.6). For example, a bias factor of 2 implies that the estimated effect based on the observed skill-specific immigration shock is twice as large as the true effect that we would obtain if we could correctly assign immigrants to skill cells. The observed shocks to each education and experience group drawn from the 2000 US Census.

Figure A.2: Illustration of the Bias in the Elasticity of Substitution between Immigrants and Natives When Immigrants Downgrade



Note: The figure illustrates the bias which may arise in estimates of the elasticity of substitution between immigrants and natives when immigrants downgrade. In the figure, immigrants and natives are assumed to be perfect substitutes in production if correctly classified to education-experience groups. The figure plots, motivated by equation (5.2) in the online appendix, the difference in the wage change of immigrants observed to be high skilled and experienced (of which some downgrade to low skilled and inexperienced jobs) and the wage change of high skilled experienced natives, divided by the observed immigration shock faced by immigrants observed to be high skilled and experienced, against the degree of downgrading by education, for three degrees of downgrading by experience (0, 0.3, and 0.6). The observed number of immigrants residing in the country and entering the country in each education-experience group come from the 2000 US Census. For each degree of downgrading by education and experience, we first calculate the true shocks to each education and experience group. We then compute the wage changes for skilled experienced natives using equation (3.5) in the online appendix and the wage changes for immigrants observed to be high skilled and experienced (which is a mixture of the wage changes of natives of all four education-experience groups).