RETHINKING THE EFFECT OF IMMIGRATION ON WAGES

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Abstract
This paper calculates the effects of immigration on the wages of native US workers of various skill levels in two steps. In the first step we use labor demand functions to estimate the elasticity of substitution across different groups of workers. Second, we use the underlying production structure and the estimated elasticities to calculate the total wage effects of immigration in the long run. We emphasize that a production function framework is needed to combine own-group effects with cross-group effects in order to obtain the total wage effects for each native group. In order to obtain a parsimonious representation of elasticities that can be estimated with available data, we adopt alternative nested-CES models and let the data select the preferred specification. New to this paper is the estimate of the substitutability between natives and immigrants of similar education and experience levels. In the data-preferred model, there is a small but significant degree of imperfect substitutability between natives and immigrants which, when combined with the other estimated elasticities, implies that in the period from 1990 to 2006 immigration had a small effect on the wages of native workers with no high school degree (between 0.6% and +1.7%). It also had a small positive effect on average native wages (+0.6%) and a substantial negative effect (−6.7%) on wages of previous immigrants in the long run. (JEL: F22, J61, J31)

1. Introduction

The empirical analysis of cross-city and cross-state evidence in the United States has consistently found small and often insignificant effects of immigration on the wages of native workers.[1] However, two recent influential contributions by Borjas (2003) and Borjas and Katz (2007) have emphasized the importance of estimating the effects of immigration using national level data and have found a significant negative effect of immigration on the wages of natives with no high school

1. See the influential review by Friedberg and Hunt (1995) and, since then, National Research Council (1997), Card (2001), Friedberg (2001), Lewis (2005), Card and Lewis (2007) and Card (2007).

diploma.[2] These studies have argued that wages across local labor markets are subject to the equalizing pressure that arises from the spatial arbitrage of mobile workers. As a result, the wage effects of immigration are better detected at the national level since one can exploit variation in wages and immigrants across groups of workers with different skills (as captured by education and experience) over time.

The underlying logic is that while it may be relatively easy for a US worker to react to local immigration by changing their residence within the United States it is much harder for her to do so by relocating across the US border or by changing her own skill mix. Accordingly, the estimation of the substitutability among workers with different skills should play a key role in the analysis of the wage effects of immigration. Our aim is to contribute to this approach at the national level in two ways: through an improved estimation of the substitutability among workers with different characteristics and through the clarification of a crucial distinction between the partial and the total wage effects of immigration, a distinction not fully appreciated in the existing literature.

First, in terms of substitutability and in contrast to Borjas (2003) and Borjas and Katz (2007), we estimate the elasticity of substitution between immigrant and native workers within the same education and experience group without assuming ex ante that they are perfectly substitutable. Given that natives and immigrants of similar education and age have different skills, often work in different jobs and perform different productive tasks, their substitutability is an empirical question, the answer to which has important implications since the degree of imperfect substitutability affects the impact that immigrants have on the wage of natives with similar skills.

Some recent papers have also estimated the native–immigrant elasticity of substitution. Card (2007), using US city data for year 2000, Raphael and Smolensky (2008), using US data over 1970–2005, and D'Amuri et al. (2010), using German data, all find small but significant values for the inverse of the native–immigrant elasticity implying less than perfect substitutability between these groups of workers (with an elasticity between 20 and 30).[3] While our estimates are in the same ballpark, a closely related work by Manacorda, Manning, and Wadsworth (this issue) using UK data finds an even smaller substitutability between natives and immigrants (with elasticity between 5 and 10). This may be due to their use of yearly net inflows (rather than the ten-year flows we use) implying that the elasticity of substitution is identified on very recent immigrants, who are likely to be the most different from natives. On the other hand, Borjas, Grogger, and Hanson (2008) show that one can get small and

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2. See, also, Borjas, Freeman, and Katz 1997.

3. In the older literature, indirect evidence of imperfect substitution between natives and immigrants was found in the form of small wage effects of immigrants on natives and larger negative effects on the wages of previous immigrants (see Longhi, Nijkamp, and Poot, 2005, pp. 468–469, for a discussion of this issue). Until very recently, however, only a very few studies have directly estimated the elasticity of substitution between natives and immigrants. Jaeger (1996) covers metropolitan areas only over 1980–1990, obtaining estimates that may be susceptible to attenuation bias and endogeneity problems related to the use of local data. Cortes (2008) considers low-skilled workers and uses metropolitan area data, finding a rather low elasticity of substitution between US- and foreign-born workers.

insignificant estimates for the inverse of the native–immigrant elasticity, and therefore little evidence of imperfect substitutability, in specifications that are highly saturated with fixed effects.[4]

We also reconsider the substitutability between workers of different schooling and experience levels. We produce new estimates and compare them with those found in the existing literature. In particular, since the inflow of immigrants to the United States in recent decades has been much larger among workers with no high school degree than among high school graduates, we emphasize the importance of distinguishing the substitutability between workers with no high school degree and workers with a high school diploma from the substitutability between those two groups taken together and workers with at least some college education. This distinction has a long tradition since Katz and Murphy (1992) argued that in order to understand the impact of changes in labor supply and demand on the wages of workers with different education levels it is important to consider highly educated and less-educated workers as imperfectly substitutable.[5] This has been motivated by the observation that the wage time series of workers with and without high school degrees move together much more than do the wages of high school dropouts and college educated workers.[6] The substitutability across alternative experience groups has been similarly investigated.[7]

Our second contribution concerns the distinction between partial and total wage effects. While the former refers to the direct impact of immigration on native wages within a skill group given fixed supplies in other skill groups, the latter accounts for the indirect impacts of immigration in all other skill groups. Accordingly, the total wage effects on natives across skill groups depend on the relative sizes of the different skill groups, the relative strength of own- and cross-skill impacts and the pattern of immigration across skill groups.

To clarify the distinction between partial and total wage effects, we introduce an aggregate production function that produces marginal productivity equations that can be used to compute both sorts of effects of immigration on the wage of natives in each skill group. Because we consider a rich set of skills, a large number of cross-skill effects need to be estimated. Doing this with minimal structure is impossible given available data. For example, the 32 education-by-experience groups proposed in Borjas (2003) and Borjas and Katz (2007) imply 992 cross-skill effects. But US Census data only consists of 192 skill-by-year observations on employment and wages. Adding structure, like the nested-CES labor composite we introduce in what follows, allows the

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4. A more detailed discussion of the results by Borjas, Grogger, and Hanson (2008) is presented in Section 4.1.

5. See also Murphy and Welch 1992; Angrist 1995; Autor, Katz, and Krueger 1998; Johnson 1997; Krusell et al. 2000; Acemoglu 2002.

6. See, for instance, Katz and Murphy (1992), p. 68, and Goldin and Katz (2008) and also Figures 7 and 8 in this paper.

7. Katz and Murphy (1992) consider a simple structure with two groups (young and old) and find an elasticity of substitution between them of around 3.3. Welch (1979) as well as Card and Lemieux (2001) use a symmetric CES structure with several age groups and estimate elasticities between 5 and 10.

plethora of cross-skill effects to be expressed in terms of a limited number of structural parameters that can, in turn, be estimated with available data. In other words, the aggregate production function provides a structural foundation to the wage regressions used to assess workers' substitutability and provides parametric interpretations of the estimated coefficients. That said, economic interpretation of estimates from any reduced-form equation requires assumptions on the form of the cross-skill interactions. So, by explicitly introducing the aggregate production function we are able to get the required estimates and we can discuss the pros and cons of the underlying assumptions.

While the nested-CES approach imposes restrictions on the form of the cross-elasticities, it is still flexible enough to allow for the exploration of alternative nesting structures in terms of number of cells, order of nesting and skill grouping. In particular, we explore four different nesting models, which together span most of the structures used to estimate the substitutability among skill groups in the existing literature. Model A augments the structure proposed by Borjas (2003, Section VII) by allowing for imperfect substitutability between US- and foreign-born workers of equal education and experience. This model assumes the same substitutability between any pair of education groups and between any pair of experience groups with identical education. While the latter assumption is standard in the labor literature, the former is rather unusual as it is more common to divide workers into two broad education groups of workers, those with high education (some college education and more) and those with low education (high school education or less).[8] This alternative partition is considered in model B. Models C and D cover plausible alternatives that are not much used by the existing literature. Model C considers the possibility that some experience groups may be closer substitutes than others by allowing for the elasticity across broad experience groups to differ from the elasticity across narrow experience groups. Finally, in model D the nesting order of education and experience in Borjas (2003, Section VII) is inverted with respect to model A.

We estimate the relevant elasticities of substitution for the four models using data from the Census in 1960, 1970, 1980, 1990, and 2000, and from the American Community Survey (ACS) 2006 downloaded from IPUMS (Ruggles et al. 2009). As this set of data generates only six time-series observations, in order to better estimate the elasticities of substitution between large aggregate groups we also use Current Population Survey (CPS) yearly data for the period 1962–2006 (downloaded from IPUMS-CPS, King et al. 2009). We then use the different nested-CES models to compute the effects of immigration on the wages of natives and previous immigrants in the period 1990–2006 based on the corresponding estimated elasticities.[9]

While overall the elasticity estimates and, therefore, the computed wage effects are somewhat sensitive to model specification, some results are robust across

8.   See, for example, Welch (1979) as well as Card and Lemieux (2001) on experience groups; Katz and Murphy (1992), Angrist (1995), Krusell et al. (2000), Goldin and Katz (2008) on education groups.

9.   In so doing, we focus on the wage effects that materialize in the long run, that is, after capital has fully adjusted to the labor supply shock caused by the inflow of foreign-born workers. See Ottaviano and Peri (2008) for the evaluation of the short-run effects.

specifications. First, we find a small but significant degree of imperfect substitutability between natives and immigrants within the same education and experience group. When we constrain the native–immigrant elasticity to be the same for all education groups, our preferred estimate is 20. It becomes much lower (around 12.5) for less educated workers once we remove that constraint. Using model A, such large but finite elasticities imply that the negative wage impact of immigration on less-educated natives is -1.1% to -2.0% over the period 1990–2006. This model would imply a wage loss of less educated natives of -3.1% when the elasticity of substitution between natives and immigrants is infinite, as in Borjas (2003) and Borjas and Katz (2007). Hence, allowing for imperfect substitutability reduces the impact of immigration on native wages by no less than a third. This imperfect substitutability also implies that, on average, immigrants already in the United States suffer much larger wage losses than natives as a consequence of inflows of new immigrants. Based on model A, their average wage losses due to immigration are calculated to be around 6.7% for the period 1990–2006.

Second, while model A is a useful tool to assess the effects of introducing imperfect native–immigrant substitutability in the framework proposed by Borjas (2003), the data suggest that model B should be preferred instead. The key evidence for this is gathered when the different models are estimated on CPS data. That sample is large enough to allow for the separate estimation of the elasticity of substitution between broad education groups and between narrow education groups. These elasticities are indeed estimated to be quite different from each other, with the first evaluated around 2 and the second evaluated above 10. Using these estimates in model B generates wage effects that are rather different from those obtained from model A. In particular, the effect of immigration on the wages of natives with low education is now a small positive effect (between 0.6% and 1.7%). This result is due to the balanced inflow of immigrants between the broad high-education and low-education groups together with the imperfect substitutability between natives and immigrants, especially those with low education levels.

Finally, there is not much support for model C as the elasticity across broad experience groups is not very different from the elasticity across narrow experience groups (both being estimated around 5). There is no reason to favor model D either, as this leads to similar parameter estimates as model A. Indeed, for given parameter estimates, both models C and D generate wage effects that are very similar to those of model A.

The rest of the paper is organized as follows. In Section 2 we introduce the aggregate production function and the alternative nested-CES models. We also derive the equations used to estimate workers' substitutability as well as those needed to calculate the partial and total effects of immigration on wages. Section 3 presents the data and describes how we compute the relevant variables. Section 4 details the empirical estimation of the relevant elasticities of substitution among different groups of workers. Section 5 uses the estimated elasticities in the alternative models to compute the wage effects of immigration. Section 6 concludes.

2. Theoretical Framework

We treat immigration as a labor supply shock, omitting any productivity impact that it may produce (due, for example, to improved efficiency, choice of better technologies, or scale externalities). We may therefore miss part of its positive impact on wages, often identified as a positive average wage effect on natives in cross-city or cross-state analyses such as Card (2007) and Ottaviano and Peri (2005, 2006b).[10] Moreover, we focus on the effects of immigration on wages in the long run, that is, after capital has fully adjusted to the labor supply shock caused by the inflow of foreign-born workers.[11]

In order to evaluate the effects of immigrants on wages, we need a model of how the marginal productivity of a given type of worker reacts to changes in the supply of other types. The model we adopt is based on the nested-CES approach that has become the workhorse for the evaluation of the wage response to labor supply and demand shocks at the national level (see, for example, Katz and Murphy 1992; Card and Lemieux 2001; Borjas 2003; Borjas and Katz 2007). This is based on an aggregate production function that parameterizes the elasticity of substitution between different types of workers together with a simple theory of capital adjustment.

2.1. Aggregate Production and Capital Accumulation

Aggregate production takes place according to the following constant-returns-to-scale Cobb–Douglas function:

$$Y = AL^{\alpha}K^{1-\alpha}, \tag{1}$$

where Y is aggregate output, A is exogenous total factor productivity (TFP), K is physical capital, L is a CES aggregate of different types of labor (more on this in Section 2.2), and $\alpha \in (0, 1)$ is the income share of labor. All variables are relative to time t but their time dependence is left implicit to alleviate the notational burden. The functional form (1) has been widely used in the macro-growth literature (recently, for instance, by Jones 2005; Caselli and Coleman 2006) and is supported by the empirical observation that the share of income going to labor is rather constant in the long run and across countries (Kaldor 1961; Gollin 2002).[12] Profit maximization under perfect competition implies that the effect of physical capital on wages operates through its effect on the marginal productivity of L whose remuneration absorbs $\alpha A(K/L)^{1-\alpha}$ units of aggregate output.

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10.   Our method may also miss any potential aggregate negative productivity effect of immigration.

11.   See Ottaviano and Peri (2008) for a discussion of short-run effects.

12.   The Cobb–Douglas functional form implies that physical capital has the same degree of substitutability with each type of worker. Some influential studies (for example, Krusell et al. 2000) have argued that physical capital complements highly educated workers and substitutes for less educated workers. This assumption, however, implies that the income share of capital should have risen over time following the large increase in the supply and the income share of highly educated workers. This has not happened in the United States over the period considered.
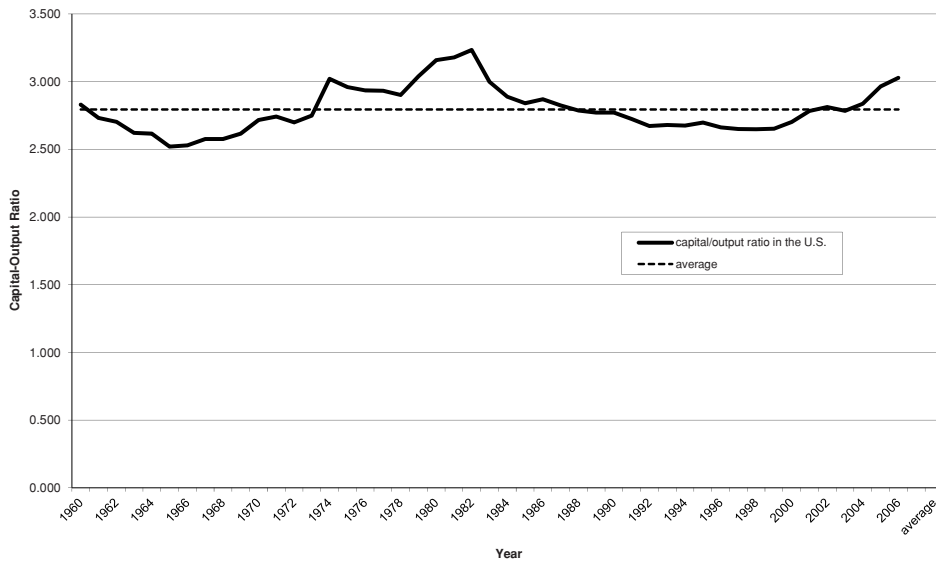
FIGURE 1. US capital–output ratio 1960–2006. Source: Authors' calculations using BEA data on the stock of physical capital and GDP.

When nested into standard Ramsey (1928) or Solow (1956) models, the production function (1) also implies that in the long run the economy follows a balanced growth path, along which the real interest rate and the aggregate capital–output ratio are both constant while the capital–labor ratio K/L grows at a constant rate equal to $1/\alpha$ times the growth rate of TFP. The intuition behind this result is that a rise in labor supply makes capital relatively scarce. This boosts its marginal productivity and depresses the marginal productivity of labor. As a reaction, capital accumulation increases until the capital–labor ratio is brought back to its balanced growth path. This implication is also supported by the data, as the real return to capital and the capital–output ratio in the United States do not exhibit any trend over the long run, while the capital–labor ratio grows at a constant rate. This is shown in Figures 1 and 2 for the period 1960–2004: both the capital–output ratio and the detrended log capital–labor ratio exhibit cyclical movements but also a remarkable mean reversion in the long run. Hence, at the aggregate level the average wage does not depend on labor supply and, therefore, on immigration in the long run. This implication of the model will be maintained throughout the paper.

2.2. Worker Heterogeneity in a Flexible Nested-CES Model

As workers are heterogeneous, the zero effect of immigration on the average wage may hide asymmetric effects at more disaggregated levels. In qualitative terms, immigrants should put downward pressure on the wages of workers with similar characteristics and upward pressure on the wages of workers with different characteristics. In quantitative
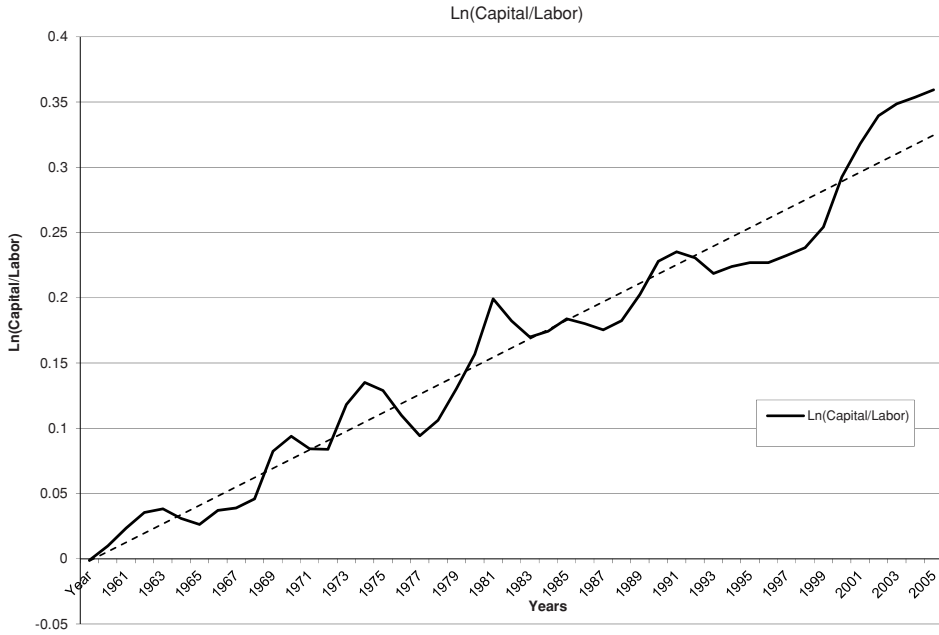
FIGURE 2. Log capital–labor ratio and trend 1960–2006. Source: Authors' calculations using BEA data on the stock of physical capital and BLS data on total nonfarm employment.

terms, these effects on wages should depend on how substitutable workers of different types are and how large the inflow of workers of each type is.

We propose a flexible nested-CES structure that embeds various alternative models studied in the literature as special cases. Though slightly demanding, the chosen notation has the advantage of allowing for recursive expressions of general results. Consider $N + 1$ characteristics numbered $n = 0, \ldots, N$. Characteristic 0 is common to all workers and defines them as such. We first partition workers into groups $i_1 = 1, \ldots, M_1$ that differ according to characteristic 1. Then, each of these groups is itself partitioned into groups $i_2 = 1, \ldots, M_2$ that differ according to characteristic 2, and so on up to characteristic N. This sequential partitioning and its relative notation is illustrated in Figure 3. The index $n = 0, \ldots, N$ identifies the characteristic used to partition workers into the corresponding groups. The figure shows how groups i_{n+1} are *nested* in groups i_n so that we can use n to also index the nesting level along the depicted partitioning structure.

Let us call $i(n)$ a group (*type*) of workers defined by common characteristics up to n, and define as $L_{i(n)}$ the corresponding labor supply. The CES aggregator at the generic level n is then defined:

$$
L_{i(n)} = \left[\sum_{i(n+1) \in i(n)} \theta_{i(n+1)} \left(L_{i(n+1)} \right)^{\frac{\sigma_{n+1}-1}{\sigma_{n+1}}} \right]^{\frac{\sigma_{n+1}}{\sigma_{n+1}-1}}, \quad n = 0, \ldots, N, \quad (2)
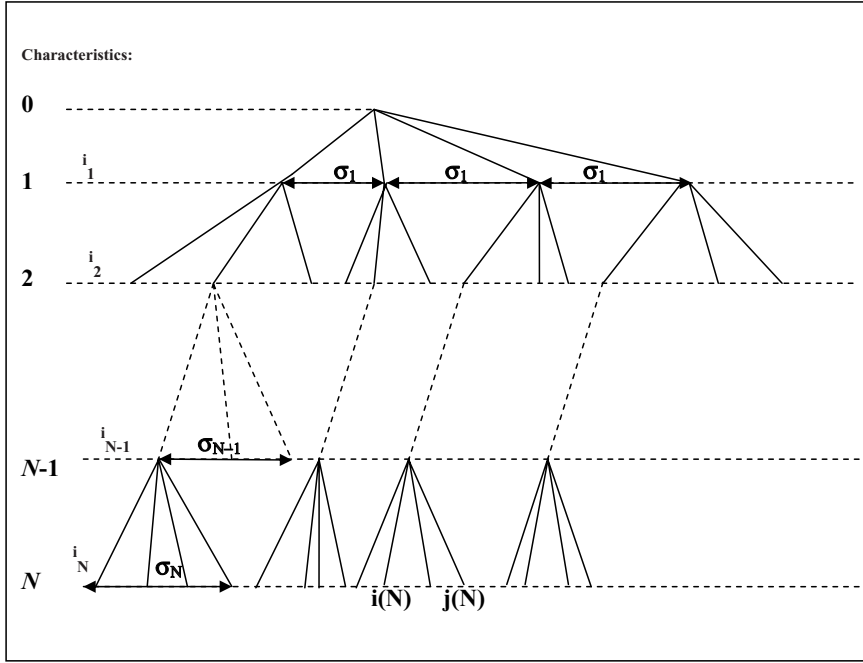$$

FIGURE 3. Scheme of the CES nests and relative notation.

where $\theta_{i(n)}$ is the relative productivity level of type $i(n)$ standardized so that $\sum_{i(n) \in i(n-1)} \theta_{i(n)} = 1$ and any common multiplying factor is absorbed in the TFP parameter A of (1). Both A and $\theta_{i(n)}$ depend on exogenous technological factors only. The parameter $\sigma_n > 0$ is the elasticity of substitution between types $i(n)$. The fact that the sequential partitioning of workers leads to fewer and fewer heterogeneous groups $i(n)$ as n increases is captured by assuming that $\sigma_{n+1} > \sigma_n$. Since type $i(0)$ includes all workers, we can embed the nested structure defined by (2) in (1) by imposing $L = L_{i(0)}$.

Using this structure and notation, we can calculate the profit-maximizing wage of a worker of type $i(N)$ as the value of her marginal productivity:

$$\ln(w_{i(N)}) = \ln(\alpha A \kappa^{1-\alpha}) + \frac{1}{\sigma_1} \ln(L) + \sum_{n=1}^{N} \ln \theta_{i(n)}$$

$$- \sum_{n=1}^{N-1} \left(\frac{1}{\sigma_n} - \frac{1}{\sigma_{n+1}} \right) \ln(L_{i(n)}) - \frac{1}{\sigma_N} \ln(L_{i(N)}). \qquad (3)$$

This expression holds for $N > 2$ and can be used as the empirical basis for estimating the substitutability parameters σ_n with $n = 1, \ldots, N$. First, focusing on the last level of nesting N and considering two different groups $i(N)$ and $j(N)$ with all characteristics

up to $N - 1$ in common, expression (3) implies

$$\ln\left(\frac{w_{i(N)}}{w_{j(N)}}\right) = \ln\frac{\theta_{i(n)}}{\theta_{j(n)}} - \frac{1}{\sigma_N}\ln\left(\frac{L_{i(N)}}{L_{j(N)}}\right). \tag{4}$$

Therefore, $-1/\sigma_N$ can be estimated from observations on wages and employment levels over time, using fixed-type effects to control for $\ln(\theta_{i(n)}/\theta_{j(n)})$. Second, for any other nesting level $m = 1, \ldots, N - 1$, we can define $w_{i(m)}$ as the average wage of a specific group of workers $i(m)$ sharing characteristics up to m. Then, substituting m for N in (3) gives the profit maximizing relation between $w_{i(m)}$ and $L_{i(m)}$. In this case, using observations over time, the estimation of $-1/\sigma_m$ can be achieved by regressing the logarithmic wage of group $i(m)$ on the logarithmic CES aggregate $L_{i(m)}$ with the inclusion of fixed-time effects to capture the variation of the aggregate terms $\ln(\alpha A\kappa^{1-\alpha})$ and $\ln(L)$, and group-specific effects varying only over characteristics up to $m - 1$ and by year in order to absorb the terms $\sum_{n=1}^{m-1}(1/\sigma_n - 1/\sigma_{n+1})\ln(L_{i(n)})$ that do not change with characteristic m.

Once we have estimated the elasticities of substitution between different types of workers, the wage equation (3) can also be used to compute the percentage change in the wage of workers of a certain type $j(N)$ caused by a percentage change in the labor supply of workers of another type $i(N)$. To show this in a compact way let us denote by $s_{i(N)}^n$ type $i(N)$'s share of the labor income among workers exhibiting the same characteristics up to n as that type. Hence, $s_{i(N)}^{n-1} \leq s_{i(N)}^n$ and $s_{i(N)}^N = 1$. Then, we can write the percentage impact of a change in labor supplied by workers of type $i(N)$ on the wage of a worker of type $j(N)$ with the same characteristics up to m as

$$\frac{\Delta w_{j(N)}^0/w_{j(N)}^0}{\Delta L_{i(N)}/L_{i(N)}} = \frac{s_{i(N)}^0}{\sigma_1} > 0, \quad m = 0 \tag{5}$$

and

$$\frac{\Delta w_{j(N)}^m/w_{j(N)}^m}{\Delta L_{i(N)}/L_{i(N)}} = -\sum_{n=0}^{m-1}\frac{s_{i(N)}^{n+1} - s_{i(N)}^n}{\sigma_{n+1}} < 0, \quad m = 1, \ldots, N. \tag{6}$$

Two remarks on equations (5) and (6) are in order. First, an increase in the labor supply of a certain type $i(N)$ causes an increase in the wage of another type $j(N)$ only if the two types differ in terms of characteristic 1. Second, if the two types share at least characteristic 1, then a rise in the labor supply of $i(N)$ always depresses the wage of $j(N)$. This effect is stronger the larger the number of differentiating characteristics $j(N)$ has in common with $i(N)$. Both results rely on the characteristics having been nested, so that $\sigma_{n+1} > \sigma_n$.

2.3. Alternative CES Nesting Structures

The traditional characteristics used in the literature to partition heterogeneous workers are education and experience (see, for example, Borjas 2003; Borjas and Katz 2007).

We consider birthplace ("US-born", "foreign-born") as an additional characteristic differentiating workers in the same education and experience categories.

There are several reasons for adding this new source of heterogeneity since, even when considering workers with equivalent education and experience, natives and immigrants differ in several respects that are relevant to the labor market. First, people who migrate are different from those that do not. Immigrants have skills, motivations and tastes that may set them apart from natives. Second, in manual and intellectual work they have culture-specific skills (for example, cooking, crafting, opera singing, soccer playing) and limits (for example, limited knowledge of the language or culture of the host country), which create comparative advantages in some tasks and comparative disadvantages in others.[13] Third, due to comparative advantages, migration networks, or historical accidents, immigrants tend to choose different occupations with respect to natives, even for given education and experience levels. In particular, new immigrants tend to work disproportionately in those occupations where foreign-born workers are already over-represented.[14] Finally, there is no need to impose perfect substitutability between natives and immigrants ex ante as this elasticity can be estimated. Hence, while exploring alternative nesting structures for education and experience, we always consider the birthplace of the worker as her Nth differentiating characteristic. This allows us to partition each education by experience cell into US-born workers (labeled D, for domestic) and foreign-born workers (labeled F).

In combining education and experience, we borrow different nesting models from the literature and, where possible, we test one against the other to allow the data to identify a preferred one. These alternative models are depicted in Figure 4 as specific cases of the flexible nested-CES model presented in Section 2.2. Model A builds on Borjas (2003) and Borjas and Katz (2007). In this model we have $N = 3$; education is characteristic 1 partitioned into four categories:

$i_1 = $ (No Degree, High School Degree, Some College Education, College Degree);

experience is characteristic 2 partitioned into eight experience categories over a working life of 40 years:

$$i_2 = (0\text{–}5, 6\text{–}10, 11\text{–}15, 16\text{–}20, 21\text{–}25, 26\text{–}30, 31\text{–}35, 36\text{–}40);$$

birthplace is characteristic 3 partitioned, as already mentioned, into two categories $i_3 = (D, F)$.

An alternative partitioning of education is more frequently used in the labor literature.[15] Accordingly, in model B workers are first partitioned in terms of two

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13.   See Peri and Sparber (2009) for evidence supporting the existence of different comparative advantages in production tasks between US- and foreign-born workers.

14.   Ottaviano and Peri (2006a) find a positive and very significant correlation between the initial share of immigrants in an occupation and the inflow of new immigrants in that occupation over the subsequent decade.

15.   See among others Goldin and Katz 2008; Katz and Murphy 1992; Autor, Katz, and Krueger 1997; Krusell et al. 2000; Card and Lemieux 2001; Acemoglu 2002; Caselli and Coleman 2006.
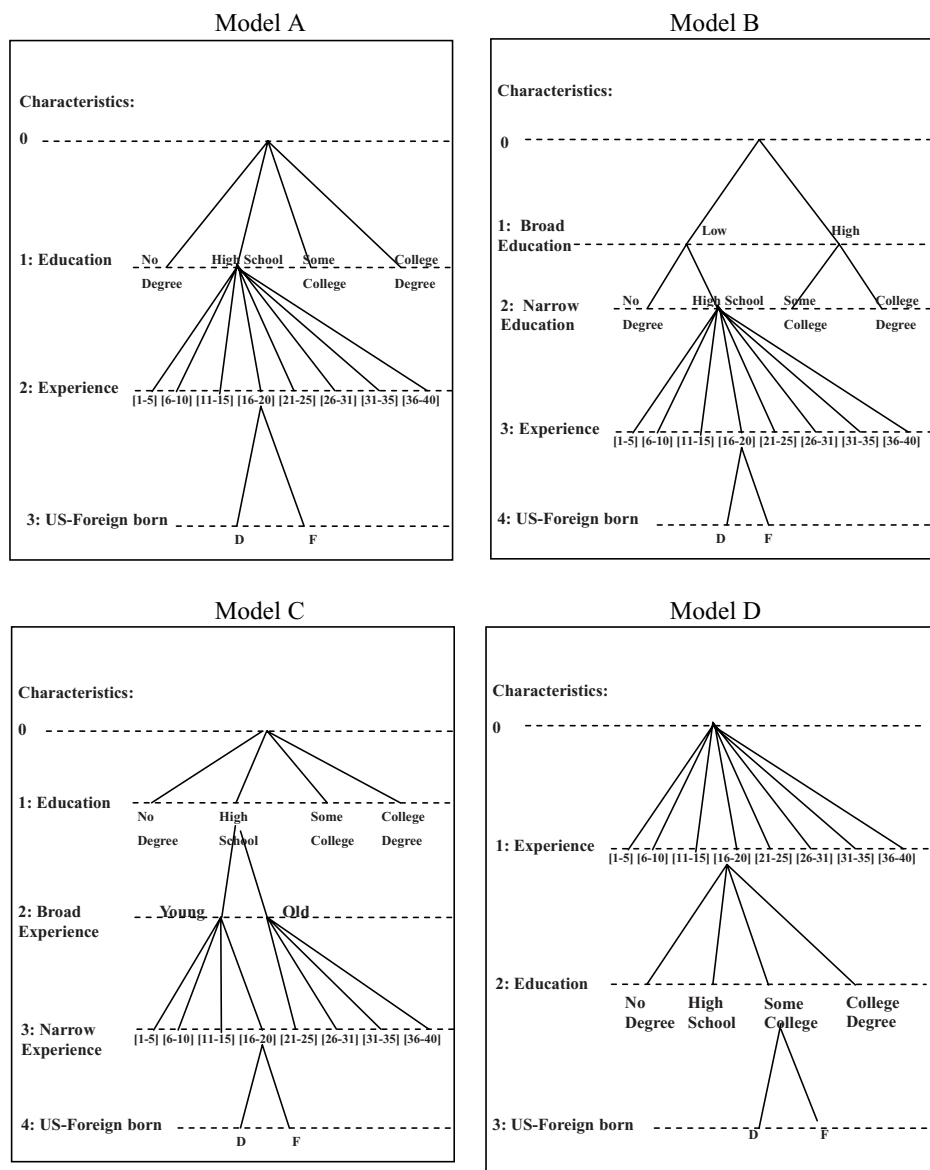
FIGURE 4. Alternative nesting models.

broad educational characteristics, each of which comprises two narrower educational categories. In this case, we have $N = 4$ with broadly defined education being characteristic 1 so that $i_1 =$ (High education, Low education). Narrowly defined education is characteristic 2, with $i_2 =$ (No degree, High school degree) partitioning Low education and $i_2 =$ (Some college education, College degree) partitioning High

education. Experience is characteristic 3, still partitioned into the same eight categories as before, and place of birth is characteristic 4.

Model C is based instead on the mirror idea that substitutability may differ across pairs of experience rather than education categories, and will be smaller for groups that are closer in terms of experience. We again have $N = 4$ but there is only one level of educational characteristics, again with four categories as in model A. Broad experience is characteristic 2 with $i_2 = $ (Young, Old) and narrow experience is characteristic 3 with $i_3 = $ (0–5, 6–10, 11–15, 16–20) within the group Young and $i_3 = $ (21–25, 26–30, 31–35, 36–40) within the group Old.

These three models all proceed from the idea that characteristics are chosen to sequentially nest groups that are increasingly substitutable ($\sigma_{n+1} > \sigma_n$). As we will see, this is consistent with our estimates implying that the elasticity of substitution across education groups is generally smaller than across experience groups. If, however, workers of different education levels were more substitutable with each other than workers of different experience levels, an inverted order of nesting would be more appropriate. Hence, we also consider model D, which reverses the nesting order between education and experience. This is a natural check, though we are not aware of previous studies that adopt it. Specifically, model D maintains the same categories as model A for both education and experience but defines experience as characteristic 1 and education as characteristic 2. The structure is completed by the place of birth as a last category so that $N = 3$.

2.4. Partial and Total Wage effects of Immigration

The flexible nested-CES model from Section 2.2 allows us to clarify a crucial distinction between partial and total wage effects. While the former refer to the direct impact of immigration within a given group of workers, the latter also account for the indirect impact of immigration on all other groups of workers. This implies that the total wage effect on natives across groups depends on the relative sizes of the different groups, the relative strength of own- and cross-group impacts, and the actual pattern of immigration across all groups.

Specifically, recall that birthplace is the Nth characteristic in all our nesting structures so that σ_N always represents the elasticity of substitution between native and immigrant workers with similar education and experience. We call the *direct partial wage effect* of immigration the wage impact on native workers due to a change in the supply of immigrants with the same $N - 1$ characteristics, while keeping constant the labor supplies of all other workers. This effect has been the main or only coefficient of interest in most *reduced-form* approaches that regress native wages on the employment of immigrants in the same skill-groups.[16] The direct partial wage effect has been

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16. For instance, in Borjas (2003, sections II to VI) or in Borjas (2006) and in the studies inspired by these seminal papers, the *direct partial wage effect* of immigration is the main estimated wage effect. Even the recent meta-study by Longhi, Nijkamp, and Poot (2005) considers this partial effect as the relevant estimate across studies.

estimated by panel regressions of $\ln w_{j(N)}^{N-1}$ on $\ln L_{i(N)}$, where the former is the wage of group $j(N)$ of native workers sharing $N-1$ characteristics (i.e., all but the birthplace) with the group $i(N)$ of immigrants and the latter is the employment of group $i(N)$ of immigrants. Careful econometric specifications (such as Borjas 2003) control for year-specific effects (to absorb the variation of $L = L_{i(0)}$) and characteristic-by-year specific effects (to absorb the variation of $L_{i(n)}$ for $n = 1, \ldots, N-1$). In terms of our flexible model, the resulting partial elasticity can be written as

$$\varepsilon_{i(N)}^{N-1} = -\left(\frac{1}{\sigma_{N-1}} - \frac{1}{\sigma_N}\right) s_{i(N)}^{N-1}. \tag{7}$$

Note, however, that the direct partial wage effect (7) coincides only with the last among the several terms composing the summation in (6) as this includes both direct and indirect wage effects. This happens because, by construction, the elasticity $\varepsilon_{i(N)}^{N-1}$ captures only the wage effect of a change in labor supply operating through the term $-(1/\sigma_{N-1} - 1/\sigma_N)\ln(L_{i(N-1)})$ in (3).

Hence, two important observations on (7) are in order. First, $\varepsilon_{i(N)}^{N-1}$ is negative whenever the chosen nesting structure is such that the substitutability between immigrants and natives sharing $N-1$ characteristics is larger than the substitutability between workers sharing only $N-2$ characteristics (that is, $\sigma_N > \sigma_{N-1}$). Second, the value and the sign of $\varepsilon_{i(N)}^{N-1}$ give incomplete information about the overall effect of immigrant supply changes on the wages of domestic workers. Indeed, (7) includes only the last term of (6), which itself is only one of the terms entering the *total wage effect* for domestic workers of type $j(N)$. In order to evaluate the total wage effect, one has to combine the impacts generated by (6) across all the $i(N)$ that include foreign-born workers for which $L_{i(N)}$ changes due to immigration.

This definition of the total wage effect implies that it cannot be directly estimated from a regression.[17] In particular, one can directly estimate the elasticities σ_1 to σ_N as well as $\varepsilon_{i(N)}^{N-1}$. However, in order to compute the total wage effect of immigration, one needs to combine the estimated elasticities σ_n with the income shares $s_{i(N)}^n$ in equation (6) and aggregate across all groups for which $L_{i(N)}$ changes due to immigrants. Intuitively, this depends on the fact that the total wage effect can only be computed by combining *own*-group effects with the set of *cross*-group effects.

To see how misleading it can be to use the direct partial wage effects to infer the total wage effects of immigration consider, for instance, model A with an elasticity of substitution between experience categories equal to 0.20 and an elasticity of

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17.   Dustmann, Frattini, and Preston (2008) propose an estimate of the *total wage effect* of immigrants on natives in a specific portion (cell) of the native wage distribution by regressing the wage of natives in that cell on the total inflow of immigrants (plus several controls). Such an approach, however, assumes the same wage effect of immigrants in any other group on natives. This is consistent with a one-level CES (which they assume) but not with a nested CES. A nested CES implies different effects depending not only on total immigration but also on the distribution of immigrants across skill groups. Moreover, to obtain enough observations for their estimates, they consider UK provinces as separate labor markets. Considering one national labor market, as we do here, would not provide enough observations (only one per year) to estimate the *total wage effect*.

substitution between natives and immigrants equal to 0.05, which we will use as reasonable estimates for the United States over our observation period 1990–2006. Assume further that the share of immigrant employment in an education group is similar to its share in the wage bill of the group. Then, (7) implies that an inflow of immigrants increasing labor supply in an education–experience group by 1% would produce a −0.15% change in the real wage of native workers in that group. If one failed to realize the partial nature of the above elasticity, one could be tempted to generalize these findings by arguing that, over the period 1990–2006, the increase of 11.4% in total hours worked in the United States due to immigration caused a decrease of −1.7% = (−0.15 ∗ 11.4%) in the average wages of natives; or that groups, such as high school dropouts, for which the inflow of immigrants was as high as 23% of initial hours worked, lost −3.4% of their wages. Such generalization would, however, be incorrect since expression (7) only accounts for the effect on wages of immigrants in the same skill group and omits all the cross-group effects. In fact, as we will detail in Section 5, while sharing the same negative partial elasticity, the wage effects on natives were very different across skill groups, depending on the relative size of the groups, the relative strength of cross-group effects, and the actual pattern of immigration across groups. As a result, the values of −1.7% or −3.4% calculated earlier do not bear any resemblance to the total wage effects.

3. Data, Variables and Sample Description

The definitions of variables, their construction and the sample selection coincide exactly with those in Borjas, Grogger, and Hanson (2008).[18] The data we use are downloaded from the integrated public use microdata samples (IPUMS) where the original sources are the US Decennial Census 1960–2000 and the 2006 American Community Survey (Ruggles et al. 2009). Following the Katz and Murphy (1992) tradition we construct two somewhat different samples to produce measures of hours worked (or employment) by cell and average wages by cell. The employment sample is more inclusive as it aims at measuring the hours worked in each education–experience–birthplace cell. The wage sample is more restrictive as it aims at producing a representative average wage (price of labor) in the cell.

   To construct the measure of hours worked in each cell and year we consider people aged 18 and older in the Census year not living in group quarters, who worked at least one week in the previous year. We then group them into four schooling groups, eight potential experience groups and two birthplace (US- and foreign-born) groups. Four schooling groups are identified: individuals with no high school degree, high school graduates, individuals with some college education, and college graduates. Years of potential experience are calculated under the assumption that people without

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18. For further details see Appendix B and the companion technical appendices available online (called Online Appendix). Together with exhaustive information on data, variable definitions and sample selection, the online appendices also provide the files and code needed to reproduce all the results in this paper.

a high school degree enter the labor force at age 17, people with a high school degree enter at 19, people with some college enter at 21, and people with a college degree enter at 23. We group workers into eight five-year experience intervals beginning with those with one to five years of experience and ending with those with 36 to 40 years of experience.[19] The status of *foreign-born* is given to those workers who are noncitizens or are naturalized citizens. We calculate the hours of labor supplied by each worker and then multiply them by the individual weight (PERWT) and aggregate within each education–experience group. This measure of hours worked by cell is the basic measure of labor supply. As an alternative measure of supply, we calculate the employment level (that is, count of employed people) by cell summing up the person weights for all people in the cell.

To construct the average wage in each cell we use a more selective sample. The basic wage sample is a subset of the employment sample where workers who do not report wages (or report 0 wages) and those who are self-employed are eliminated. In a more restrictive wage sample we only include full-time workers, defined as those working at least 40 weeks in the year and at least 35 hours in the usual workweek.[20] The average weekly wage in a cell is constructed by calculating the real weekly wages of individuals (equal to annual salary and income, INCWAGE, deflated using the CPI and adjusted for top-coding, divided by weeks worked in a year) and then taking their weighted average where the weights are the hours worked by the individual times her person weight.

The procedure just described allows us to construct the variables *hours worked* or *employment* and *average weekly wages* for all groups defined by their education, experience, and nativity characteristics in each year *t* (1960, 1970, 1980, 1990, 2000, 2006). The data also allow us to construct the wage bill share of each group and subgroup. When estimating the elasticity parameters, we always use the entire panel of data, 1960–2006. When we compute the effects of immigration on real wages based on those estimates, we focus on the most recent period, 1990–2006.

Table 1 reports the percentage increase in hours worked due to immigrants (column 3) and the percentage change in weekly wages of natives (column 4) for each education–experience group over the period 1990–2006, pooling men and women together. This period is the one on which we focus for our assessment of the total wage effects of immigration. Even a cursory look at the values in column 3 of Table 1 reveals that the inflow of immigrants has been uneven across groups. Focusing on the rows marked All Experience Groups, in each of the four narrow educational groups we notice that the group of workers with no high school degree experienced the largest percentage increase in hours worked due to immigrants over the 1990–2006 period (equal to +23.6%) followed by the group of college graduates (+14.6%), while high

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19.   Workers with 0 years of potential experience or less and with more than 40 years of potential experience are dropped from the sample.

20.   This sample excludes workers with low *labor market attachment* who could be different from full-time workers and whose average weekly wage can introduce nonclassical measurement error, as argued by Borjas, Grogger, and Hanson 2008.

TABLE 1. Immigration and changes in native wages: education-experience groups, 1990–2006.

Column 1: Education	Column 2: Experience	Column 3: Percentage change in hours worked in the group due to new immigrants 1990–2006	Column 4: Percentage change in weekly wages, Natives, 1990–2006
No High School Degree (ND)	1 to 5 years	8.5%	0.7%
	6 to 10 years	21.0%	−1.5%
	11 to 15 years	25.9%	0.6%
	16 to 20 years	31.0%	1.6%
	21 to 25 years	35.7%	1.3%
	26 to 30 years	28.9%	−1.6%
	31 to 35 years	21.9%	−8.8%
	36 to 40 years	14.3%	−10.1%
	All Experience groups	**23.6%**	**−3.1%**
High School Degree (HSD)	1 to 5 years	6.7%	−5.3%
	6 to 10 years	7.7%	−1.6%
	11 to 15 years	8.7%	−1.4%
	16 to 20 years	12.1%	1.8%
	21 to 25 years	13.0%	0.6%
	26 to 30 years	11.8%	−0.9%
	31 to 35 years	11.0%	−2.0%
	36 to 40 years	9.3%	−4.0%
	All Experience groups	**10.0%**	**−1.2%**
Low Education (ND+HSD)	**All Experience groups**	**13.2%**	**−1.5%**
Some College Education (SCO)	1 to 5 years	2.6%	−5.4%
	6 to 10 years	2.6%	−2.0%
	11 to 15 years	3.9%	0.1%
	16 to 20 years	6.2%	0.6%
	21 to 25 years	8.4%	−2.5%
	26 to 30 years	12.0%	−3.1%
	31 to 35 years	12.3%	−3.8%
	36 to 40 years	12.7%	−3.0%
	All Experience groups	**6.0%**	**−1.9%**
College Degree (COD)	1 to 5 years	6.8%	0.4%
	6 to 10 years	12.2%	6.5%
	11 to 15 years	13.7%	14.2%
	16 to 20 years	12.2%	17.3%
	21 to 25 years	17.5%	9.1%
	26 to 30 years	24.4%	4.3%
	31 to 35 years	26.1%	1.7%
	36 to 40 years		
	All Experience groups	**14.6%**	**9.3%**
High Education (SCO+COD)	**All Experience groups**	**10.0%**	**4.5%**

school graduates and the group of workers with some college education experienced only a 10% and a 6% increases, respectively. Interestingly, however, such imbalances are drastically reduced if we consider the broad educational categories corresponding to High Education and Low Education as defined in Section 2.3. When we merge workers with a high school degree and those with no degree (see the row in the middle of Table 1) immigrant labor represents a 13.2% increase in hours worked (1990–2006). This is because the group of high school graduates received few immigrants and the group of workers with no degree constitutes only a very small share of the total labor supply.[21] In comparison, merging workers with some college education and those with a college degree implies that immigration represented a 10% increase in hours worked by the High Education group (last row of Table 1). Therefore, it is already clear from these numbers that the substitutability between the group of workers with no degree and those with a high school degree will be very important in determining how much of the downward pressure of immigrants on wages remains localized in the group of workers with no degree and how much is instead diffused to the group of workers with at most a high school degree. This suggests that the extra degree of flexibility allowed by model B in Figure 1 may be very important to correctly evaluate the total wage effects of immigration.

Column 4 of Table 1 shows the percentage change of real weekly wages in each education–experience group between 1990 and 2006. A cursory comparison of columns 3 and 4 of Table 1 suggests that it would be hard to find a strong negative correlation between increases in the share of immigrants and the real wage changes of natives across the narrow education groups. We are now ready to use our model to check whether this obviously superficial and possibly wrong prima facie impression survives deeper scrutiny.

4. Elasticity Estimates

4.1. Place of Birth

We begin with the estimation of the elasticity of substitution between natives and immigrants sharing all education and experience characteristics. As discussed in Section 2.3, in all our nesting models the place of birth is the Nth characteristic and σ_N is the corresponding elasticity of substitution (hence, intuitively N can be seen also as a mnemonic for *nativity*). Moreover, in all our nesting models we have the same 32 skill groups at level $N - 1$ (4 narrow education categories times 8 narrow experience categories). This allows us to implement equation (4) for all models through the following common empirical specification:

$$\ln\left(\frac{w_{Fkt}}{w_{Dkt}}\right) = \varphi_k + \varphi_t - \frac{1}{\sigma_N}\ln\left(\frac{L_{Fkt}}{L_{Dkt}}\right) + u_{it}, \tag{8}$$

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21. Only 8% of total hours worked in 2006 are supplied by workers with no degree versus 30% by workers with a high school degree.

where w_{Dkt} and w_{Fkt} are the average wages of natives and immigrants in group k with k spanning all the 32 skill (education by experience) groups in Census year t. L_{Dkt} and L_{Fkt} are the corresponding hours worked (or employment). Expression (8) assumes that relative productivity $\ln(\theta_{Fkt}/\theta_{Dkt})$ in skill group k can be represented as $\varphi_k + \varphi_t + u_{it}$ where φ_k is a set of 32 education–experience effects, φ_t is a set of six year effects, and u_{it} are zero-mean random variables uncorrelated with relative labor supply $\ln(L_{Fkt}/L_{Dkt})$ (more on this in what follows). Accordingly, φ_k captures the relative productivity of foreign-born versus natives workers of similar education and experience. We allow relative productivity to have a common component of variation over time φ_t across groups, due for instance to changes in immigration policies. We also assume that the remaining time variation u_{it} is independent of relative labor supply. While imposing specific restrictions on the behavior of relative productivity, these assumptions seem reasonable. First, since we use *ratios* of wages and labor supply within education–experience groups, any variation of group specific efficiency in a Census decade would cancel out. In particular, any biased technological change affecting the productivity of more educated (experienced) workers relative to less educated (experienced) workers would be washed out in the ratios. Second, our assumptions are still less restrictive than those made in the existing literature to similarly estimate the elasticity of substitution between skill groups.[22]

Before commenting on the regression results reported in Table 2, it is useful to have a preliminary look at the data. Figure 5 shows the scatterplot of $\ln(w_{Fkt}/w_{Dkt})$ versus $\ln(L_{Fkt}/L_{Dkt})$ and the corresponding regression line from a simple OLS estimation including all 32 education–experience groups in all the years considered. The negative and significant correlation between relative wages and relative labor supplies provides prima facie evidence of imperfect substitutability. The elasticity σ_N implied by the OLS coefficient is around 20 and precisely estimated. Figure 6 shows the scatterplot restricted to the groups of workers with no degree, which have experienced the largest percentage immigrant inflows over the period. In this case the negative correlation is even stronger and more significant with the OLS coefficient, implying an elasticity of substitution σ_N of about 14.

This first impression of imperfect substitutability between natives and immigrants is confirmed in Table 2 which reports the values of $-1/\sigma_N$ estimated using specification (8). Each entry in the table corresponds to a point estimate from a different regression and the standard errors, reported in parentheses below the estimates, are heteroskedasticity robust and clustered by education–experience group to allow error correlation within group. The method of estimation is Least Squares. In specifications 1, 2, 4, and 5 we weight each cell by its employment in order to down-weight those cells with large sampling errors (due to their small size). Specifically, columns (1) and

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22. For instance, in estimating the elasticity of substitution between experience groups, Borjas (2003, Section VII.A) and Borjas and Katz (2007, Section 1.4) assume that, within each education category, the experience-specific productivity terms are constant over time. This would correspond to including only φ_k in our regression. In Katz and Murphy (1992) the elasticity of substitution between education groups is estimated by assuming that the evolution of their relative productivity follows a time trend. This would correspond to restricting our φ_t to follow a time trend.

TABLE 2. Estimates of the coefficient $(-1/\sigma_N)$.

Specification	(1) No Fixed Effects	(2) With FE	(3) Not weighted with FE	(4) No Fixed Effects	(5) With FE	(6) Not weighted with FE
Wage Sample:	All workers, weighted by hours			Full time workers only		
PANEL A **Estimates of $(-1/\sigma_N)$.**						
Men	−0.053***	−0.033**	−0.045***	−0.063**	−0.048***	−0.059***
	(0.008)	(0.013)	(0.013)	(0.005)	(0.010)	(0.012)
Women	−0.037***	−0.058***	−0.067***	−0.050***	−0.066***	−0.071***
	(0.009)	(0.017)	(0.016)	(0.007)	(0.014)	(0.012)
Pooled Men and Women	−0.032***	−0.024*	−0.026**	−0.044***	−0.037***	−0.038**
	(0.008)	(0.015)	(0.015)	(0.006)	(0.012)	(0.013)
Men, Labor supply measured as employment	−0.057**	−0.027**	−0.030**	−0.066***	−0.040**	−0.041**
	(0.007)	(0.014)	(0.015)	(0.006)	(0.012)	(0.014)
PANEL B **Separate estimates of $(-1/\sigma_N)$ by education group.**						
Men, No degree	−0.073***	−0.070***	−0.070***	−0.085***	−0.084**	−0.081**
	(0.007)	(0.010)	(0.009)	(0.004)	(0.006)	(0.007)
Men, High School Graduates	−0.089***	−0.090***	−0.093***	−0.097***	−0.099***	−0.100***
	(0.016)	(0.020)	(0.018)	(0.013)	(0.015)	(0.015)
Men, Some College education	−0.071**	−0.060	−0.070*	−0.077**	−0.068*	−0.075**
	(0.024)	(0.035)	(0.034)	(0.023)	(0.033)	(0.034)
Men; College Graduates	−0.017	0.006	0.019	−0.024	−0.009	−0.0150
	(0.026)	(0.042)	(0.030)	(0.027)	(0.041)	(0.029)

TABLE 2. Continued.

Specification	(1) No Fixed Effects	(2) With FE	(3) Not weighted with FE	(4) No Fixed Effects	(5) With FE	(6) Not weighted with FE
Wage Sample:	All workers, weighted by hours			Full time workers only		
	PANEL C					
	Separate estimates of $(-1/\sigma_N)$ by experience group					
Men, 0–10 years of experience	−0.012	−0.14***	−0.15**	−0.037**	−0.151***	−0.157***
	(0.018)	(0.028)	(0.030)	(0.014)	(0.020)	(0.031)
Men, 11–20 years of experience	−0.044**	−0.061***	−0.066**	−0.050***	−0.068***	−0.073***
	(0.011)	(0.014)	(0.013)	(0.011)	(0.014)	(0.014)
Men, 21–30 years of experience	−0.073**	−0.052**	−0.058**	−0.077***	−0.059**	−0.066***
	(0.008)	(0.022)	(0.017)	(0.007)	(0.022)	(0.018)
Men, 31–40 years of experience	−0.094**	−0.065**	−0.063**	−0.096***	−0.064***	0.060**
	(0.013)	(0.014)	(0.016)	(0.013)	(0.015)	(0.018)

Note: National Census and ACS, U.S. data 1960–2006. Each cell reports the estimate of the parameter -1/σ_N from specification (8) in the text. Method of estimation is Least Squares. In parentheses we report the heteroskedasticity-robust standard errors, clustered over the 32 education-experience groups. In specifications 1, 2, 4 and 5 we weight each cell by its employment. FE (fixed Effects) include Education by Experience plus time effects in rows one to four, Experience fixed effects are included in rows 5 to 8 and Education fixed effects are in rows 9–12. *** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level.
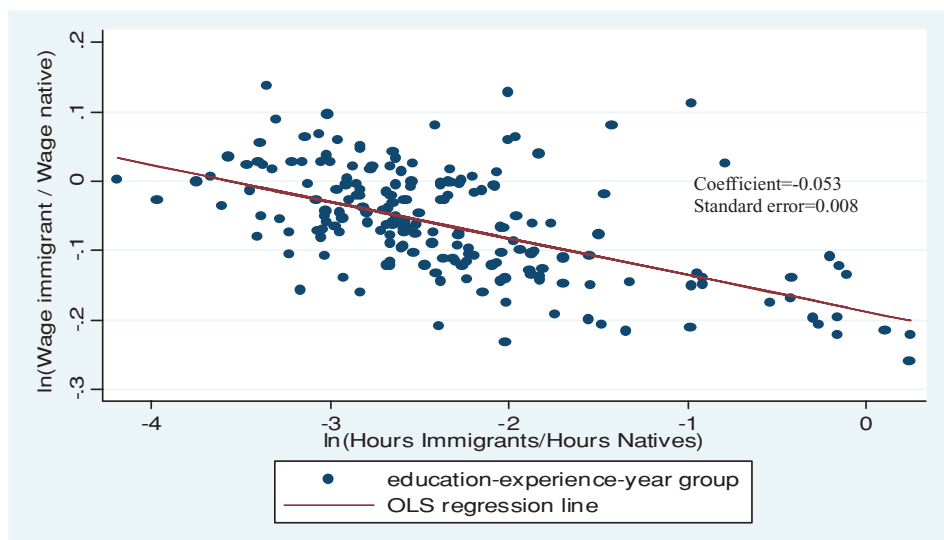
FIGURE 5. Correlation between relative wages and hours worked, immigrant-natives. Cells are education–experience–year groups. Men, 1960–2006.

Note: Each observation corresponds to one of the 32 education–experience group in one of the considered years (1960, 1970, 1980, 1990, 2000, 2006). The horizontal axis measures the logarithm of the relative hours worked in the group by male immigrants relative to natives and the vertical axis measure the logarithm of the weekly wage paid to male immigrants relative to natives.

(4) report the estimates obtained without including the fixed effects φ_k and φ_t in the regression, while other columns always include them. In columns (3) and (6), instead, we use OLS without weighting the cells. Moreover, in columns (1) to (3) all (non-self-employed) workers are used to construct the wage sample while in columns (4) to (6) only full time workers are used. Turning to rows, the top four rows show the coefficient estimates obtained for the whole sample (192 observations), assuming that σ_N is the same for each group. The subsequent rows explore the possibility that σ_N varies across education groups (Rows 5 to 8) or across different experience groups (Rows 9 to 12). In addition, the top four rows show the coefficients obtained by focusing alternatively on male relative wages (Row 1), female relative wages (Row 2) or pooled relative wages (Row 3). Finally, the fourth row uses employment, rather than hours worked, as the measure of the relative labor supply.

Two clear results emerge from the estimates reported in Panel A of Table 2. First, in each case the estimated coefficient $-1/\sigma_N$ is significantly negative at the 5% level, and in most cases at the 1% level. Second, the estimated values range between -0.024 and -0.071. Most of them are around -0.05 implying estimates of σ_N in the neighborhood of 20. Somewhat larger estimates of $-1/\sigma_N$ in absolute value are obtained when using the sample of full-time workers and of women, but these differences are not significant. To test robustness along other dimensions, we have also performed additional estimates (not reported but available upon request): excluding the early period of data (1960s) or the most recent period (2000–2006), clustering the standard errors over education
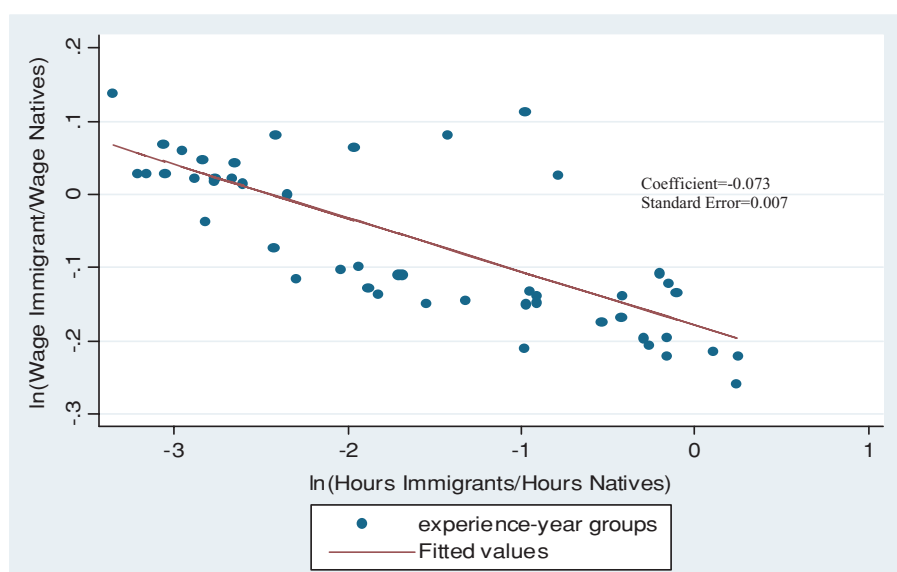
FIGURE 6. Correlation between relative wages and hours worked, Immigrant–natives with no degree; cells are experience–year groups, male with no degree only, 1960–2006

Note: Each observation corresponds to one of the 32 education–experience group in one of the considered years (1960, 1970, 1980, 1990, 2000, 2006). The horizontal axis measures the logarithm of the hours worked in the group by male immigrants relative to natives and the vertical axis measure the logarithm of the weekly wage paid to male immigrants relative to natives.

groups (or experience groups) only, or weighting the cells by hours rather than total employment. None of the resulting estimates is much different in size and statistical significance from those reported in Table 2.

For the estimates of $-1/\sigma_N$ to be consistent, relative productivity have to be uncorrelated with relative labor supplies after controlling for the fixed effects. Our structural model only calls for education–experience fixed effects.[23] Immigrant-biased productivity shocks concentrated in some cells, however, may attract more immigrants to those cells, thus inducing a positive correlation between relative productivity and labor supply. This would cause OLS to be upward biased and the bias would be more severe the larger the correlation. In this case, our estimates would represent an upper bound for the true value of $-1/\sigma_N$ so that the actual elasticity σ_N would be even smaller than what is implied by our estimates.

To control for some systematic types of correlation of the error with the explanatory variables over time and across groups, one can include additional specific effects. Borjas, Grogger, and Hanson (2008) in a specification otherwise similar to (8) include education-by-time and experience-by-time effects. Accordingly, they estimate 102 fixed effects with 192 observations and a very large part of the panel variation is absorbed by the fixed effects. This increases the standard errors, which become mostly

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23.   As in the estimation of the other elasticities, we only include the effects required by the model.

larger than 0.03 and often as large as 0.04, posing problems in identifying a coefficient $-1/\sigma_N$ that is mostly estimated in the neighborhood of -0.05.

Specifically, let us consider their preferred specifications (for pooled men and women) which include all workers, weighted by hours worked, or full time workers only. These are reported in columns (2) and (3) of their Table 4, which show estimates of $-1/\sigma_N$ equal to 0.005 and -0.034 respectively, with associated standard errors of 0.024 and 0.036. Our corresponding estimates can be found in columns (2) and (5) of Panel A of Table 2 and are equal to -0.024 and -0.037 respectively, with associated standard errors of 0.015 and 0.012. An important difference lies in the standard errors, which are significantly larger in Borjas, Grogger, and Hanson (2008), implying that both of our point estimates are well within two standard deviations of theirs. Based on these results, Borjas, Grogger, and Hanson (2008) conclude that there is no compelling evidence of imperfect substitutability. However, given the size of their standard errors, they can rarely reject values of $-1/\sigma_N$ equal to -0.05, so that there is no compelling evidence either of perfect substitutability. As a result, and since, as we will see in Section 5, even a small degree of imperfect substitutability makes a significant difference in terms of the computed effects of immigration on native wages, we prefer our point estimates and standard errors as reported in Table 2.[24]

Imperfect substitutability between immigrants and natives of similar observable characteristics may derive from somewhat different skills among these groups leading to different choices of occupations. Peri and Sparber (2009) suggests that this is particularly true for low levels of education since these immigrants tend to have less English language skill. Since they do have similar physical and manual skills as natives they tend to specialize in manual-intensive tasks. This does not happen at high levels of education because the skills of college-educated workers are more similar between native and immigrants. Moreover, since the difference in skills tends to decrease the longer immigrants stay in the United States, imperfect substitutability could be particularly acute among young workers. For both reasons the estimated elasticity of substitution should be smaller for young and less-educated workers. In Table 2, Panel B shows the estimates of $-1/\sigma_N$ when we restrict the sample to cells including, alternatively, workers with no degree (first row of Panel B), a high school degree (second row), some college education (third row), or a college degree (fourth row). Each of the estimates is based on 48 observations (8 experience groups times 6 years) and controls for experience fixed effects (except specifications in columns (1) and (4)). Interestingly, the estimates of $-1/\sigma_N$ for the groups up to "Some college

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24.   Two recent studies have estimated $-1/\sigma_N$ for countries different from the United States using specifications similar to (8) but relying on even fewer dummies as controls. D'Amuri, Ottaviano, and Peri (2010) for Germany and Manacorda, Manning, and Wadsworth (this issue) for the UK both include only education, experience and time effects. As for their estimated values, while the results in D'Amuri, Ottaviano, and Peri are similar to ours, Manacorda, Manning, and Wadsworth find lower native–immigrant substitutability. This is possibly due to the fact that they identify the native–immigrant elasticity of substitution on yearly data, thus including among immigrants only the newest arrivals, who are likely to be the most different in skills and abilities from natives.

education" are very significant and between -0.06 and -0.10, with an average value around -0.08. They imply an average elasticity of substitution of 12.5. For college educated workers, on the other hand, there is no evidence of imperfect substitutability. Although not very precise, the estimate of $-1/\sigma_N$ for this group is very close to 0. Panel C of Table 2 shows the estimates when pooling education groups and separating cells for workers with potential experience up to 10 years (Row 9), 11 to 20 years (Row 10), 21 to 30 years (Row 11), or 31 to 40 years (Row 12). Each coefficient is estimated using 48 observations (4 education times 2 experience groups times 6 years). The estimates are in this case mostly significant. When we control for education fixed effects we also observe the predicted pattern according to which $-1/\sigma_N$ is larger in absolute value for the youngest group (-0.15 with corresponding elasticity of substitution 6.6) than for the others (-0.06 with corresponding elasticity of substitution 16.6).

To sum up, when the substitutability between natives and immigrants is constrained to be the same across education and experience groups, the estimated elasticity of substitution σ_N is about 20. When we allow for differences across education and experience groups, we find that natives and immigrants have a particularly low substitutability among low educated workers ($\sigma_N = 12.5$) and among young workers ($\sigma_N = 6.6$).

4.2. Education and Experience

We have used equation (8) to estimate $-1/\sigma_N$. From the same regression we also obtain estimates of the fixed effects φ_k . These can be translated into estimates of the systematic (time-invariant) component of immigrant and native productivities, $\hat{\theta}_{F,k} = \exp(\hat{\varphi}_k)/(1 + \exp(\hat{\varphi}_k))$ and $\hat{\theta}_{D,k} = 1/(1 + \exp(\hat{\varphi}_k))$ respectively, which can be used to construct the labor composite $L_{i(N-1)}$ for group $i(N-1)$ using formula (2) for $n = N - 1$.[25] We can then calculate the corresponding average wage $w_{i(N-1)}$ and estimate $-1/\sigma_{N-1}$ by implementing equation (3). In so doing, we include two types of fixed effects. The first controls for the variation of the common aggregate term $\ln(\alpha A\kappa^{1-\alpha}) + (1/\sigma_1)\ln(L)$ and group-specific aggregates $\sum_{n=1}^{N-2}(1/\sigma_n - 1/\sigma_{n+1})\ln(L_{i(n)})$. The second controls for the systematic variation of group-specific productivities $\ln\theta_{i(N-1)}$.

The first type of fixed effect is dictated by the nested-CES structure and, therefore, depends on the chosen nesting model.[26] The second type is, instead, required by the fact that the variation of $\ln\theta_{i(N-1)}$ may be correlated with $L_{i(N-1)}$, which would affect the consistency of the estimates. As the theoretical framework has no implication as to which specific effects to include in order to control for such a correlation, we simply assume that while $\ln\theta_{i(N-1)}$ may have a systematic component across groups

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25. In the derivation of the expressions for $\hat{\theta}_{F,k}$ and $\hat{\theta}_{D,k}$ we have used the standardization $\hat{\theta}_{F,k} + \hat{\theta}_{D,k} = 1$.

26. For instance, in model A the common aggregate term can be controlled for by time effects whereas $\ln L_{i(N-2)}$ can be captured by education-by-time effects.

potentially correlated with the distribution of $L_{i(N-1)}$, the remaining variation over time is a zero-average random variable uncorrelated with changes in $L_{i(N-1)}$, and we add some structure over time (such as time trends). This method can be iterated upward so that, once we have the estimates of σ_n and $\ln \theta_{i(n)}$, we can construct $L_{i(n-1)}$ and $w_{i(n-1)}$ and proceed to estimate σ_{n-1} by applying (3) to level $n-1$.

Let us emphasize that while we estimate the elasticity σ_{N-1} (and higher level elasticities σ_n with $n = 1, \ldots, N-2$) by implementing (3), the interpretation of the elasticity σ_{N-1} and the type of fixed effects included depend on the nesting structure chosen. While so far our recursive notation has proved useful in order to embed the alternative nesting models in a single flexible nested-CES framework, the comparative discussion of estimated elasticities across models will benefit from a more intuitive notation. Say, for example, that we want to compare the estimated substitutability between narrow experience groups. Depending on the model, the corresponding elasticity would be σ_{N-1} (models A, B and C) or σ_{N-2} (model D). Hence, from now on we prefer to label the various elasticities by the name of the relevant characteristics rather than by their order in the nesting structure. Of course each elasticity coming from the different nesting models is estimated using the appropriate specification of (3) and includes the appropriate set of fixed effects prescribed by the corresponding structure. Henceforth, σ_{EXP} will denote the elasticity of substitution between five-year experience groups and will be estimated for all models; σ_{Y-O} will denote the elasticity of substitution between twenty-year experience groups and, therefore, will be estimated only for model C; σ_{EDU} will denote the elasticity of substitution between narrow education groups and, therefore, will be estimated for all models; and σ_{H-L} will denote the elasticity of substitution between high- and low-education workers and, therefore, will be estimated only for specification B.

Before presenting our estimates, two comments are in order. First, in the existing literature there are estimates of all these elasticities. In particular, σ_{Y-O} and σ_{EXP} have been estimated by Welch (1979), Katz and Murphy (1992) and Card and Lemieux (2001) while σ_{H-L} and σ_{EDU} have been estimated by Katz and Murphy (1992) and Goldin and Katz (2008). This means that our estimates and those in the literature can be used to inform the choice of parameters for the computation of total wage effects in Section 5. Second, as we estimate elasticities at higher levels of the nesting structure (especially σ_{H-L}), we end up using only a few large labor aggregates for which the Census data provide very few observations over time (six year points only). For this reason, we complement the estimates that use Census data with estimates obtained on data from the Current Population Survey (CPS) 1963–2006, which provides 44 yearly observations.

4.2.1. Census Data.   First, let us discuss our estimates of the elasticities of substitution for experience groups using Census data. Table 3 reports the estimates of the parameters $-1/\sigma_{\text{EXP}}$ and $-1/\sigma_{Y-O}$ obtained for the different nesting structures by implementing the appropriate version of equation (3). All regressions are estimated using 2SLS and immigrant labor supply to instrument total labor supply (measured as

TABLE 3. Estimates of $(-1/\sigma_{\text{EXP}})$.

Structure of the nest	Model A and B	Model C		Model D
	(1)	**(2)**	**(3)**	**(4)**
Estimated coefficient:	$(-\mathbf{1}/\sigma_{\text{EXP}})$	$(-\mathbf{1}/\sigma_{\text{EXP}})$	$(-\mathbf{1}/\sigma_{\text{Y}-\text{O}})$	$(-\mathbf{1}/\sigma_{\text{EXP}})$
Men	−0.16***	−0.19**	−0.31*	−0.30***
Labor Supply is Hours worked	(0.05)	(0.08)	(0.15)	(0.06)
Women	−0.05	−0.08*	−0.14	−0.01
Labor Supply is Hours worked	(0.05)	(0.045)	(0.12)	(0.06)
Pooled Men and Women	−0.14***	−0.17**	−0.28**	−0.23***
Labor Supply is Hours worked	(0.04)	(0.06)	(0.12)	(0.05)
Men	−0.13***	−0.18**	−0.26*	−0.22***
Labor Supply is Employment	(0.05)	(0.08)	(0.12)	(0.06)
Cells:	Education-experience-year	Education-experience-year	Education-Young/Old-year	Experience-year
Effects Included	Education by Year and Education by Experience	Education-Young-Year, Education-Old-Year and Education by Experience	Education-Year and Education-Young/Old	Experience effects and year effects
Observations	192	192	96	48

Note: National Census and ACS U.S. data 1960–2006. Each cell reports the estimates from a different regression that implements equation (3) in the text for the appropriate characteristics and using the appropriate aggregate and fixed effects. The method of estimation is 2SLS using immigrant workers' hours as an instrument for total workers' hours. Cells are weighted by their employment. Standard errors are heteroskedasticity robust and clustered at the education-experience level for columns (1) and (2), at the education-young/old level for column (3) and at the experience level for column (4).
*, **, *** = significant at the 10, 5 and 1% level.

hours worked or employment) in the relevant labor composite[27]. As in Section 4.1, we are assuming that, after controlling for the fixed effects, the variation of immigrants by cell is random and orthogonal to relative productivity changes. As before, rows 1 to 3 report the estimates obtained using men, women, or both in the wage sample whereas row 4 uses employment rather than hours worked as measure of labor supply. The other rows report the cells, the fixed effects, and the number of observations included in the various specifications. In estimating $-1/\sigma_{\mathrm{EXP}}$, models A and B generate exactly the same regression equation, for which estimates are reported in column (1). Model C produces estimates of $-1/\sigma_{\mathrm{EXP}}$ at level $N-1$ and of $-1/\sigma_{Y-O}$ at level $N-2$. These are in columns (2) and (3), respectively. Model D generates estimates of $-1/\sigma_{\mathrm{EXP}}$ at level $N-2$, which are reported in column (4).

There is some variation in the estimates depending on the sample and the model. In particular, estimates using the wage sample of women are never significant. The estimates for men and for the pooled sample are, however, remarkably consistent, always significantly different from 0 and averaging around -0.20. The wage sample of women may have a significant amount of error. Women often have a more discontinuous working career than men, so potential experience may be a noisy proxy of actual experience. For this reason most studies (see, for example, Card and Lemieux 2001) focus on men only and, when considering women, one should expect an attenuation bias. The other estimates vary between -0.13 and -0.31, which is exactly the range previously estimated in the literature for this parameter. In a setup similar to ours with five-year experience categories within education categories, Welch (1979, Tables 7 and 8) finds a value of $-1/\sigma_{\mathrm{EXP}}$ between -0.080 and -0.218. Katz and Murphy (1992, footnote 23) estimate a value of -0.342 using only two experience groups (*young*, equivalent to 1–5 years of experience and *old*, equivalent to 26–35 years of experience). Finally, in the most influential contribution, Card and Lemieux (2001, Table V) use the supply variation due to the baby boomers' cohorts to estimate a value between -0.107 and -0.237. Hence, an estimate of -0.20, which is around the middle of our range, would be also in the middle of the combined ranges of previous estimates. We take this as a reasonable reference value, implying $\sigma_{\mathrm{EXP}} = 5$.

Another overall implication of the estimates in Table 3 is that there is no strong evidence that the elasticity of substitution between broad experience groups (*young* and *old*) is lower than the elasticity between narrow five-year experience groups. The coefficient $-1/\sigma_{\mathrm{EXP}}$ is estimated in the pooled sample at -0.17 with a standard deviation of 0.06 while $-1/\sigma_{Y-O}$ for the same sample is -0.28 with a standard error of 0.12. A formal test does not reject the hypothesis of them being equal at the 10% level.[28] Thus, given that for $1/\sigma_{Y-O} = 1/\sigma_{\mathrm{EXP}}$ model C reduces to model A and no

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27. This reflects the idea that changes in immigrants' employment in each skill group, once we control for fixed effects, is mainly driven by supply shocks such as demographic factors and migration costs. Such an assumption is the common one in the literature on the national wage effect of immigrants.

28. We have also estimated $-1/\sigma_{Y-O}$ and $-1/\sigma_{\mathrm{EXP}}$ on yearly CPS data, using a method similar to Katz and Murphy (1992). This is reported in our online appendices. Doing so, we do not find evidence that those elasticities are statistically different either. Also in this case the point estimates of $-1/\sigma_{Y-O}$ and $-1/\sigma_{\mathrm{EXP}}$ are mostly between -0.1 and -0.2.

previous study has found $1/\sigma_{Y-O}$ different from $1/\sigma_{\mathrm{EXP}}$. We interpret these results as suggesting that *model C can be reasonably absorbed into model A*.

Second, let us discuss our estimates of elasticity of substitution for education groups using Census data. Table 4 shows the estimates of $-1/\sigma_{\mathrm{EDU}}$, reporting the estimates obtained from the appropriate versions of (3) for model A in columns (1) and (2) and those for model D in columns (3) and (4). The estimates for model C (not reported) are essentially identical to those obtained for model A, further confirming the coincidence between these two models. The estimates in Table 4 are very sensitive to the nesting structure adopted and to the fixed effects included. Model A prescribes the inclusion of time effects, so we either include education effects and education-specific time trends (to capture relative changes in education demand) or only education-specific time trends. Model D dictates the inclusion of experience by year effects (column (3)) but we also include education–experience and education–year effects to control for heterogeneous productivity (column (4)). We have also tried several other combinations of fixed effects and trends obtaining mostly negative, non-significant estimates. The specifications that produce significant estimates (column (2) and (3)) show values ranging between -0.22 and -0.43. The literature provides scant guidance for this parameter. The only clear comparisons we can make are with Borjas (2003), whose estimate is -0.759 (with standard error equal to 0.582), and with Borjas and Katz (2007), whose estimate is -0.412 (with standard error equal to 0.312) due to the fact that both papers use the same nesting structure as model A. The estimate in Borjas and Katz (2007) is indeed very close to those reported in column (2) of our Table 4, which uses exactly the same set of dummies and trends that they use.

Most of the literature, however, has assumed a split between two imperfectly substitutable education groups (High and Low) and has produced several estimates of the corresponding elasticity $-1/\sigma_{H-L}$. This is also assumed by our model B. Unfortunately, however, $-1/\sigma_{H-L}$ cannot be estimated with available Census data since by considering high school graduates or less as low-education workers and college-educated or more as high-education workers we are left with only twelve observations to work with. Hence, in order to obtain estimates of $-1/\sigma_{H-L}$, we revert to CPS data.

4.2.2. CPS Data. Writing (3) for model B at the highest level of nesting ($n = 1$) for $i(1) = \text{High}$ and $i(1) = \text{Low}$ and taking the ratio between the resulting expressions, we obtain

$$\ln\left(\frac{w_{Ht}}{w_{Lt}}\right) = \ln\frac{\theta_{Ht}}{\theta_{Lt}} - \frac{1}{\sigma_{H-L}}\ln\left(\frac{L_{Ht}}{L_{Lt}}\right), \tag{9}$$

where w_{Ht} is the average weekly wage of workers with a college degree or more (calculated as an hours-weighted average) and w_{Lt} is the hours-weighted average weekly wage of high school graduates or less. The parameters θ_{Ht} and θ_{Lt} capture the productivities of the two groups and L_{Ht} and L_{Lt} measure their labor supplies. Note that equation (9) is identical to the one estimated by Katz and Murphy (1992) (henceforth, simply KM).

TABLE 4. Estimates of $(-1/\sigma_{EDU})$.

Specification:	Model A		Model D	
	(1) With education-specific FE and trends	**(2)** With education-specific trends only	**(3)** With experience-year FE	**(4)** With experience-year, education-experience and education-year FE
Men Labor Supply is Hours worked	−0.16 (0.12)	−0.28** (0.10)	−0.22* (0.12)	−0.04 (0.03)
Women Labor Supply is Hours worked	−0.16 (0.15)	−0.34** (0.14)	−0.25** (0.11)	−0.02 (0.04)
Pooled Men and Women Labor Supply is Hours worked	−0.15 (0.10)	−0.30** (0.11)	−0.23** (0.11)	−0.02 (0.03)
Men Labor Supply is employment	−0.17 (0.10)	−0.43** (0.16)	−0.28** (0.09)	−0.03 (0.03)
Cells	Education-Year	Education-Year	Education-Experience-years	Education-Experience-years
Fixed Effects Included:	Education-specific effects, Education-specific trends and Year effects	Education-specific trends and Year effects	Experience by year only	Experience by year, Education by year and education by Experience
Number of observations	24	24	192	192

Note: National Census and ACS, U.S. data 1960–2006. Each cell reports the estimates from a different regression that implements (3) in the text using the appropriate wage as dependent variable and labor aggregate as explanatory variable and the appropriate fixed effects. The method of estimation is 2SLS using immigrant workers as instrument for total workers in the relative skill group. Cells are weighted by their employment. Standard errors are heteroskedasticity robust and clustered at the education level for columns (1) and (2), and at the education-experience level for columns (3) and (4).
*, **, *** = significant at the 10, 5 and 1% level.

We implement (9) on the yearly IPUMS–CPS data from King et al. (2008) with the sample and variable definitions generally identical to those used for the Census data in the previous section.[29] The data cover the period 1963–2006, so we have 44 yearly observations to estimate each elasticity. Assuming that the relative productivity $\ln(\theta_{Ht}/\theta_{Lt})$ can be decomposed into a systematic time trend and a random variable u_t uncorrelated with relative labor supply, we can estimate $-1/\sigma_{H-L}$ using OLS. There are only two small differences between our procedure and the KM one. First, our measures of labor supply L_{Ht} and L_{Lt} are CES labor composites rather than simple sums of hours. The two measures of labor supply, however, turn out to be very highly correlated so that the distinction does not matter much. Second, in KM workers with some college education contribute their hours of work partly to L_{Ht} and partly to L_{Lt} according to some regression weights. In our case all workers with some college education are included in L_{Ht}.

The estimates of $-1/\sigma_{H-L}$ based on (9) are reported in column (1) of Table 5. As in KM, we use the pooled sample of men and women and show both the heteroskedasticity-robust and the Newey–West autocorrelation-robust standard errors (as the time-series data may contain some autocorrelation). Rows 1 and 2 differ in terms of the allocation of hours worked by workers with some college education. Row 1 splits them between the high-education and the low-education groups as in KM whereas row 2 includes all workers in the former group, as implied by our model. In addition, row 3 uses employment rather than hours worked as the measure of labor supply while row 4 omits the 1960s. Finally, parentheses highlight the OLS standard errors while square brackets highlight the Newey–West autocorrelation-robust standard errors.

According to column (1), all estimates of $-1/\sigma_{H-L}$ are between -0.32 and -0.66, with standard errors between 0.06 and 0.09, hence very significantly different from 0. These estimates are close to the value estimated by KM at -0.709 with a standard error of 0.15 and confirm the imperfect substitutability between high- and low-education workers with an elasticity of substitution ranging between 1.5 and 1.8. When workers with some college education are included only in the High Education group (row 2), the estimated $-1/\sigma_{H-L}$ is -0.32, thus somewhat smaller in absolute value and compatible with an elasticity of substitution of 3. All in all, these results suggest that an elasticity around 2 (as frequently used in the literature) represents indeed a reasonable estimate of σ_{H-L}.

The KM method embedded in specification (9) is also useful to estimate the elasticities of substitution $\sigma_{\text{EDU},H}$ and $\sigma_{\text{EDU},L}$ between narrow education categories within the high- and low-education groups. In particular, in model B the ratios of equations (3) at the nesting stage $n = 2$ within the two broad groups produce the two equations that allow estimation of the inverse of those elasticities by regressing the within-group wage ratios on the corresponding within-group employment ratios,

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29. The IPUMS (Integrated Public Use Microdata Samples) produces comparable variable definitions and names between the CENSUS data (that we used in the previous sections) and CPS data. Additional information on the construction of sample and variables using CPS data can be found in Appendix B and, in greater detail, in the online appendix to this paper.

TABLE 5. Elasticity of substitution between broad and narrow education groups.

	Model B			
	(1) $-1/\sigma_{\text{H-L}}$	**(2)** $-1/\sigma_{\text{EDU,L}}$	**(3)** $-1/\sigma_{\text{EDU,H}}$	**Observations**
"Some College" split between L_H and L_L	−0.54*** (0.06) [0.07]	−0.029 (0.018) [0.021]	−0.16* (0.08) [0.10]	44
"Some College" in L_H	−0.32*** (0.06) [0.08]	−0.029 (0.018) [0.021]	−0.16* (0.08) [0.10]	44
Employment as a Measure of Labor Supply	−0.66*** (0.07) [0.09]	−0.039 (0.020) [0.024]	−0.08 (0.09) [0.11]	44
1970–2006	−0.52*** (0.06) [0.08]	0.021 (0.028) [0.025]	−0.13 (0.08) [0.09]	36

Note: CPS data 1962–2006, Pooled Men and Women. Each cell is the estimate from a separate regression using yearly CPS data. In the first column we estimate the relative wage elasticity of the group of workers with a high school degree or less relative to those with some college or more. Method and construction of the relative supply (hours worked) and relative average weekly wages are described in the text in Section 4.2.2. In the first row we split workers with some college education between H and L. In the second row we include them in group H, following the CES nesting in our model. In the second column we consider only the groups of workers with no degree and those with a high school degree (the dependent variable is relative wages and the explanatory is relative hours worked). In the third column we consider only workers with some college education and workers with a college degree or more (the dependent variable is relative wages and the explanatory is relative hours worked). In brackets are the standard errors and in square brackets the Newey-West autocorrelation-robust standard errors. *** = significant at 1% level; ** = significant at 5% level; * = significant at 10% level.

assuming that relative productivities follow a time trend plus a random term uncorrelated with relative supplies. Columns (2) and (3) of Table 5 report the estimates of $-1/\sigma_{\text{EDU,L}}$ and $-1/\sigma_{\text{EDU,H}}$.[30] Both estimates, and particularly the former, are much smaller in absolute value than $-1/\sigma_{H-L}$. In the majority of cases they are not significantly different from 0. The estimates of $-1/\sigma_{\text{EDU,L}}$ are at most equal to −0.039 and a one-sided test can exclude at any confidence level that the estimate is larger than 0.10 in absolute value. The F-test statistic for $-1/\sigma_{\text{EDU,L}} = -0.32$ (a value that corresponds to the lowest estimate of $-1/\sigma_{H-L}$) is 258, thus rejecting the null hypothesis of $-1/\sigma_{\text{EDU,L}} = -1/\sigma_{H-L}$ at an overwhelming level of confidence. The estimate of $-1/\sigma_{\text{EDU,H}}$ is around −0.10. Again, the hypotheses $-1/\sigma_{\text{EDU,H}} = -0.32$ and $-1/\sigma_{\text{EDU,H}} = -1/\sigma_{H-L}$ are rejected.

Hence, three important results emerge from Table 5. First, the restriction $-1/\sigma_{\text{EDU,H}} = -1/\sigma_{\text{EDU,L}} = -1/\sigma_{H-L}$ is overwhelmingly rejected by the data. This provides evidence that model B better fits the time-series CPS data than model A.

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30.   The corresponding estimates using wages calculated on the male sample only are available in the Table G.5 of the online appendix.
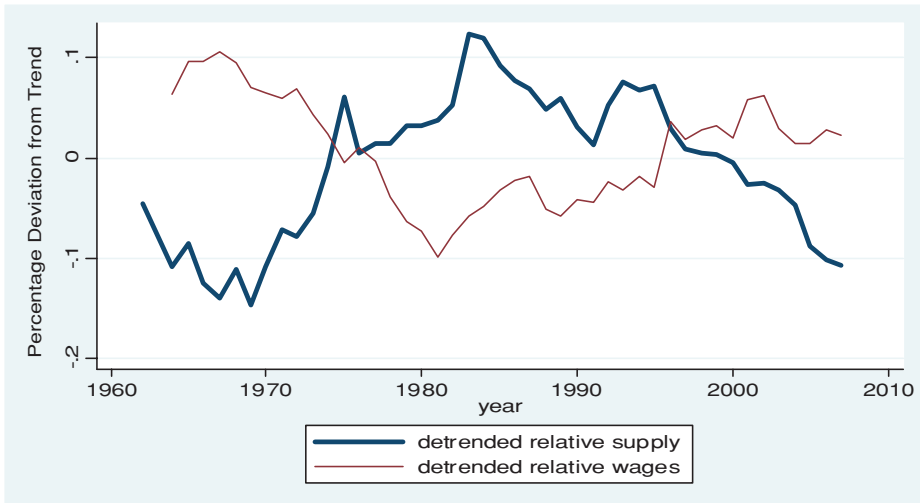
FIGURE 7. Relative supply and relative wages: (college and more)/(high school or less) 1963–2006.

Second, the estimates of $-1/\sigma_{H-L}$ are between -0.32 and -0.66 with an average of -0.50. This implies $\sigma_{H-L} = 2$, which is perfectly in line with the estimates of Katz and Murphy (1992), Angrist (1995), Johnson (1997), and Krusell et al. (2000) which range between 1.5 and 2.5. Third, the estimated value of $-1/\sigma_{\mathrm{EDU},L}$ is between -0.039 and 0, implying an elasticity of substitution between workers with a high school degree and those with no high school degree of 25 or above.

The reason for the extremely different estimates of $-1/\sigma_{\mathrm{EDU},L}$ and $-1/\sigma_{H-L}$ is clear from the detrended time series of relative supplies (thick line) versus relative wages (thin line) of college graduates and more versus high school graduates and less (Figure 7) and of high school graduates versus high school dropouts (Figure 8). In particular, Figure 7 shows clear and strong mirror movements of the relative (detrended) wages and supplies, a clear sign of negative correlation resulting in negative and significant $-1/\sigma_{\mathrm{EDU},H}$. In contrast, Figure 8 shows no movement at all of relative wages vis à vis the very large fluctuations of the relative detrended relative supplies, which are similar in direction and larger in magnitude than those in Figure 7. This results in a value of $-1/\sigma_{\mathrm{EDU},L}$ close to 0.

To sum up, CPS data suggest that reasonable estimates are in the neighborhood of -0.5 for $-1/\sigma_{\mathrm{EDU},H}$ and between -0.10 and 0 for $-1/\sigma_{\mathrm{EDU},L}$ and $-1/\sigma_{\mathrm{EDU},H}$ with the first coefficient closer to 0 and the second closer to -0.10. Accordingly, while one should be cautious in interpreting these values given the sensitivity of the estimates to specifications and nesting structures, the pattern that emerges seems to suggest that model B is preferred by the data to model A, with σ_{H-L} around 2 and $\sigma_{\mathrm{EDU},H}$ and $\sigma_{\mathrm{EDU},L}$ both larger than or equal to 10.
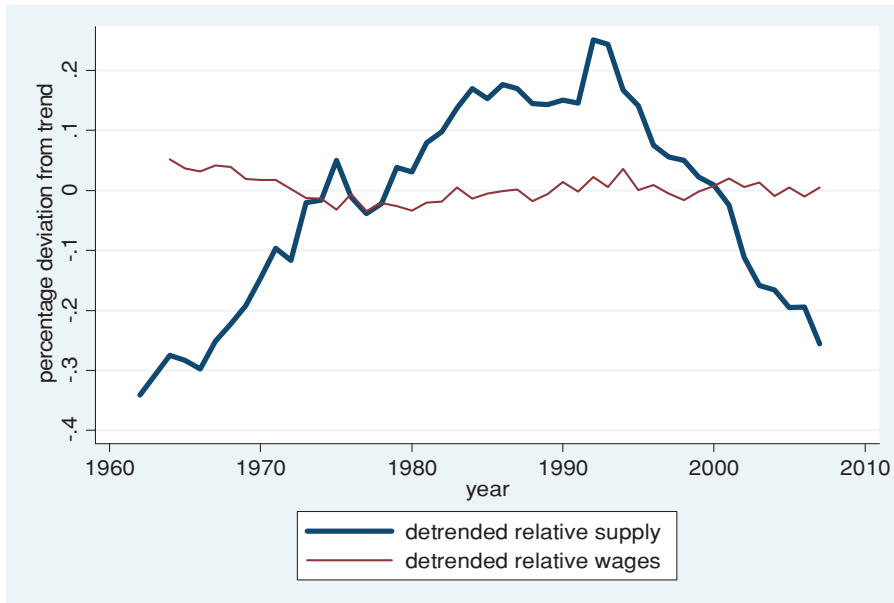
FIGURE 8. Relative supply and relative wages: (college and more)/(high school or less)
1963–2006.

5. Wage Effects of US Immigration

In Section 4 we have presented a new set of estimated elasticities of substitution between workers with different education, experience, and place of birth. In particular, we have argued in favor of a common elasticity of substitution σ_{EXP} (in the range of 5.5 to 6.25) between any pair of experience groups, and for an elasticity of substitution σ_N around 20 between natives and immigrants with the same education and experience, with some evidence that if one allows σ_N to vary between more and less educated, the corresponding elasticities become 33 and 11.1 respectively. The support for a common σ_{EXP} has led us to subsume model C in model A. Moreover, the findings against a common elasticity of substitution σ_{EDU} between different pairs of education groups have led us to prefer model B to both model A and model D with an elasticity of substitution σ_{H-L} around 2 between broad education groups, and elasticities of substitution $\sigma_{\text{EDU},H}$ and $\sigma_{\text{EDU},L}$ around 6.25 and 33.3 respectively. On the other hand, if one still wanted to use models A and D as a robustness check, it would be reasonable to adopt an estimate of σ_{EDU} from column (2) of Table 4 of around 3.3.

Whereas, as discussed in Section 2.4, the previous literature has often focused on generally uninformative *partial* wage effects, we provide here an assessment of the *total* wage effects of immigration to the United States in the period 1990–2006 by comparing the implications of models A, B, and D based on the corresponding estimated elasticities. Specifically, we use the estimated elasticities from Tables 2 to

5 and the data on actual immigrant flows by skill group reported in column 3 of
Table 1 (together with the appropriate wage shares) to calculate the percentage impact
of immigration in any skill group on the wages of each skill group as implied by
expressions (5) and (6). We then aggregate all these impacts to obtain averages for
specific sets of workers.[31]

Table 6 reports the simulations of the total long-run wage effects of immigration
over the 1990–2006 period, separating US-born workers in panel A and foreign-born
workers in panel B. The term *long-run* implies that the simulated effects assume full
adjustment of the capital stock of the economy in order to restore the capital–labor ratio
as it was before the inflow. We focus on 1990–2006 as this was the period of fastest
immigration growth in recent US history.[32] As highlighted in the top row of the table,
we consider models A, B, and D due to the fact that, according to the data, model C can
be absorbed into model A (see Section 4.2.1). The values of the elasticities used in each
simulation are reported in the first six rows of the table. The elasticities are the estimated
parameters. They are asymptotically normal and their point estimates and standard
deviations are reported in the first rows of Table 6. We consider 1,000 draws from the
joint normal parameter distribution with the specified average and standard deviation.
Then, using the formulas for the appropriate model, we calculate the total wage effect
for each education–experience group for each draw of the parameters. This produces
1,000 simulated effects for each skill group and each parameter configuration. From
those simulated realizations we obtain the simulated average total wage effect for the
group and its simulated standard error. The reported wage change (and standard error)
in each education group for foreign- and US-born workers are obtained by weighting
the percentage total wage change (and standard errors) of each experience-education
group by its wage share in the education group.[33] This provides the entries in the rows
labeled "less than HS", "HS graduates", "Some CO", and "CO graduates", which show
the simulated total effects, averaging by education group and their simulated standard
error. We also average the changes across education groups for US- and foreign-born
workers separately, again weighting the effect in each group (and its standard error)
by their wage shares. The resulting values are reported in the rows labeled "Average
US-born" and "Average Foreign-Born". Finally, we average the changes for the two
groups of US- and foreign-born workers, still using wage share weights, to obtain
the overall wage change (and its standard deviation) reported in the last row labeled
"Overall Average".

Recall that Table 6 reports the "long-run" effects, after capital has fully adjusted
to the labor supply shock caused by immigration. Consistent with our theoretical
framework the overall average wage effect is always zero in the long run (as the
average wage depends only on the capital–labor ratio and this does not change in

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31.   The detailed formulas relative to model B are described in Appendix A.2. The formulas for the other
models are analogous. The STATA code to implement the formulas for all models are available in the
online appendix.

32.   Net immigration decreased in 2007 and 2008 and it was negative in 2009.

33.   Weighting by wage shares is dictated by the nested-CES structure.

TABLE 6. Calculated long-run wage effects of immigration, 1990–2006. (with simulated standard errors)

Nesting Structures:	Model A/C			Model D		Model B			
Parameter values (std. errors in parentheses):	(1) $1/\sigma_N = 0$	(2) Estimated $1/\sigma_N$	(3) Education specific $1/\sigma_N$	(4) Estimated $1/\sigma_N$	(5) Education specific $1/\sigma_N$	(6) Estimated $1/\sigma_N$	(7) Education specific $1/\sigma_N$	(8) Katz-Murphy $1/\sigma_{HIGH-LOW}$	(9) $1/\sigma_{EXP} = 0.13$
$1/\sigma_{H-L}$	0.30 (0.11)	0.30 (0.11)	0.30 (0.11)	0.28 (0.09)	0.28 (0.09)	0.54 (0.06)	0.54 (0.06)	0.71 (0.15)	0.54 (0.06)
$1/\sigma_{EDU,H}$	0.30 (0.11)	0.30 (0.11)	0.30 (0.11)	0.28 (0.09)	0.28 (0.09)	0.16 (0.08)	0.16 (0.08)	0	0.16 (0.08)
$1/\sigma_{EDU,L}$	0.30 (0.11)	0.30 (0.11)	0.30 (0.11)	0.28 (0.09)	0.28 (0.09)	0.03 (0.02)	0.03 (0.02)	0	0.03 (0.02)
$1/\sigma_{EXP}$	0.16 (0.05)	0.16 (0.05)	0.16 (0.05)	0.30 (0.05)	0.30 (0.05)	0.16 (0.05)	0.16 (0.05)	0.16 (0.05)	0.13 (0.05)
$1/(\sigma_N)_H$	0	0.05 (0.01)	0.03 (0.03)	0.05 (0.01)	0.03 (0.03)	0.05 (0.01)	0.03 (0.03)	0.03 (0.03)	0.03 (0.03)
$1/(\sigma_N)_L$	0	0.05 (0.01)	0.09 (0.01)	0.05 (0.01)	0.09 (0.01)	0.05 (0.01)	0.09 (0.01)	0.09 (0.01)	0.09 (0.01)

PANEL A
Real percentage change of the wage of <u>us-born workers</u> due to immigration, 1990–2006.
(simulated standard errors in parentheses)

Less than HS	−3.1 (1.0)	−2.0 (1.0)	−1.1 (1.0)	−1.8 (1.0)	−1.0 (1.0)	0.6 (0.4)	1.5 (0.4)	1.7 (0.4)	1.5 (0.5)
HS graduates	0.7 (0.3)	1.1 (0.3)	1.5 (0.3)	1.1 (0.4)	1.5 (0.4)	0.3 (0.1)	0.7 (0.1)	0.6 (0.2)	0.7 (0.1)
Some CO	1.6 (0.5)	1.9 (0.6)	1.8 (0.6)	1.8 (0.5)	1.7 (0.6)	1.3 (0.3)	1.2 (0.4)	0.3 (0.3)	1.1 (0.5)
CO graduates	−1.1 (0.5)	−0.3 (0.5)	−0.6 (0.6)	−0.2 (0.4)	0.5 (0.6)	0.3 (0.4)	0.0 (0.6)	0.6 (0.5)	0.0 (0.6)
Average US-born	0.0 (0.5)	0.6 (0.6)	0.6 (0.6)	0.6 (0.5)	0.6 (0.6)	0.6 (0.3)	0.6 (0.4)	0.6 (0.4)	0.6 (0.5)

TABLE 6. Continued

Nesting Structures:	Model A/C			Model D		Model B			
Parameter values (std. errors in parentheses):	(1) $1/\sigma_N = 0$	(2) Estimated $1/\sigma_N$	(3) Education specific $1/\sigma_N$	(4) Estimated $1/\sigma_N$	(5) Education specific $1/\sigma_N$	(6) Estimated $1/\sigma_N$	(7) Education specific $1/\sigma_N$	(8) Katz-Murphy $1/\sigma_{HIGH-LOW}$	(9) $1/\sigma_{EXP} = 0.13$

PANEL B
Real percentage change of the wage of foreign-born workers due to immigration, 1990–2006.
(simulated standard errors in parenthesis)

Less than HS	−3.1 (1.0)	−7.4 (1.4)	−10.6 (1.3)	−7.3 (1.3)	−10.5 (1.4)	−4.8 (0.9)	−8.1 (0.9)	−7.8 (0.9)	−8.1 (0.9)
HS graduates	0.7 (0.3)	−6.3 (1.4)	−11.7 (1.4)	−6.3 (1.5)	−11.8 (1.4)	−7.1 (1.4)	−12.6 (1.4)	−12.8 (1.4)	−12.6 (1.4)
Some CO	1.6 (0.5)	−2.9 (1.1)	−1.1 (2.8)	−3.1 (1.1)	−1.1 (2.7)	−3.6 (1.0)	−2.2 (2.7)	−2.6 (2.8)	−1.8 (2.9)
CO graduates	−1.1 (0.5)	−8.8 (1.6)	−5.7 (4.6)	−8.8 (1.6)	−5.6 (4.5)	−8.2 (1.6)	−5.5 (4.4)	−4.6 (4.8)	−5.3 (4.8)
Average Foreign-born	**0.0 (0.5)**	**−6.8 (1.4)**	**−6.7 (3.0)**	**−6.8 (1.4)**	**−6.7 (3.0)**	**−6.4 (1.3)**	**−6.7 (2.8)**	**−6.3 (3.0)**	**−6.4 (3.0)**
Overall average	**0.0 (0.4)**	**0.0 (0.6)**	**0.0 (0.8)**	**0.0 (0.6)**	**0.0 (0.8)**	**0.0 (0.4)**	**0.0 (0.6)**	**0.0 (0.6)**	**0.0 (0.7)**

Note: The percentage wage changes for each education group are obtained averaging the wage change of each education-experience group weighting by the wage share in the education group. The wage change for each group is calculated using the formulas for the appropriate nesting structure. Since the parameters used (listed in the first 6 rows) are normally distributed random variables we proceed as follows. We first generate 1000 extractions per each configuration of the parameters (described in the top of the column) from a joint normal distribution. We then calculate the wage effect for each education-experience group and then we take the average and the std. deviation of the 1000 values. The US-born and foreign-born average changes and their standard errors are obtained by weighting changes (and standard errors) of each education group by its share in the 1990 wage bill of the group. The overall average wage change adds the change of US- and foreign-born weighted for the relative wage shares in 1990 and it is always equal to 0 due to the long-run assumption that the capital-labor ratio adjusts to maintain constant returns to capital.

the long run). However the imperfect substitutability between natives and immigrants implies that there may be a permanent effect of immigration on the average wage of each group (as shown in the last row of panels A and B) which is, in this case, positive for natives (whose relative supply decreases) and negative for immigrants (whose relative supply increases).

Turning to the columns, column (1) shows the simulated wage effects using model A and the parameter combination estimated on Census data using model A (namely the estimates in the third row of column (2) in Table 4 and in the first row of column (1) in Table 3) except for $1/\sigma_N$, which is taken to be 0. Such a combination of parameters is close to that adopted by Borjas (2003) and Borjas and Katz (2007). Columns (2) and (3) present simulations using the same nesting model and parameter combination as column (1), except for $1/\sigma_N$ whose value is estimated. We either impose that $1/\sigma_N$ is equal for all groups, and specifically equal to 0.05 (which is roughly the average estimate in Table 2, panel A), or we allow it to differ across education groups using $1/\sigma_N = 0.09$ for those with a high school degree or less and $1/\sigma_N = 0.03$ for those with some college education or more (column (3)). These are the average estimates from Table 2, panel B. In columns (4) and (5) we use the parameter configuration estimated using model D (first row of specification 4 in Table 3 and fourth row of specification 3 in Table 4) and the formulas from model D to produce the simulated values. Columns (6), (7), and (9) show the results obtained using the parameter configuration estimated with model B when, as estimated in Section 4.2.2, substitutability is significantly lower between broad education groups than between narrow education groups within the same broad group. Specifications 6 and 7 use the estimates from the first row of Table 5 and differ only in their treatment of $1/\sigma_N$ as equal across all groups or as education-specific. Specification 9 uses an alternative, smaller estimate of $1/\sigma_{\text{EXP}}$. Finally, column (8) uses the elasticity between education groups from Katz and Murphy (1992) and the other parameters from our model B estimates. Those authors estimate a value of $1/\sigma_{H-L}$ equal to 0.71 and perfect substitution within broad education groups.

Let us first compare the results reported in column (1), in which natives and immigrants are perfect substitutes, with those in columns (2) or (3), in which they are instead imperfect substitutes. Three main differences emerge. First, the wage loss of the least-educated native workers is reduced by 1.1 or 2 percentage points. Given that in column (1) the negative wage impact is estimated at -3.1 percentage points, that loss is reduced between one- and two-thirds of its absolute value. Accounting for the uncertainty of the effects, captured by the simulated standard errors, the wage loss of less-educated natives is not significant in column (3) and marginally significant in column (2). Second, on average, all the other native groups gain a bit more (or lose a bit less) in columns (2) and (3) relative to column (1). In fact, natives as a whole gain 0.6% of their average wage in columns (2) and (3) (although the gain is not significantly different from 0 if we account for the standard error). Third, the gains of natives in columns (2) and (3) relative to column (1) happen at the expense of previous immigrants as these bear most of the competitive pressure from new immigrants due to their perfect substitutability. This is the relevant distributional shift due to immigration

and imperfect substitutability: on average, natives gain 0.6 to 0.7% of their wages whereas previous immigrants lose 6.6 to 7% of their wages. The losses of immigrants are statistically significant at a 1% confidence level if we use the simulated standard error and a normal two-sided test.

The results for model D in columns (4) and (5) are quite similar to those of model A. This is because the estimated elasticities across education and nativity groups are similar. Moreover, for given elasticities, the order of nesting between education and experience has little bearing on the wage effects. In particular, the losses of natives with low or intermediate education seem a bit attenuated but the gaps are small. Otherwise, the three main differences with respect to column (1) apply to these cases too.

Finally, columns (6)–(9) report the wage effects in model B, which Section 4.2.2 has shown to be preferred by the data. In light of the estimates in that section, columns (6), (7), and (9) set $1/\sigma_{H-L} = 0.54$, $1/\sigma_{EDU,H} = 0.16$ and $1/\sigma_{EDU,L0W} = 0.03$, assuming imperfect substitutability between natives and immigrants to be either equal across groups (column (6)) or education-specific (columns (7) to (9)). Column (8) uses $1/\sigma_{H-L} = 0.71$, which is the exact estimate from Katz and Murphy (1992), and in column (9) we test how sensitive the results are to changing $1/\sigma_{EXP}$ to 0.13. The wage effects are not too different across all columns. Interestingly, the wage effects on less-educated natives are usually small but are positive and sometimes significant, especially when one allows the lower substitutability between natives and immigrants among less educated workers (columns (7) to (9)). Natives still gain as a group (0.6% of their average wages) and immigrants still lose (−6.1%). The main difference with columns (2) or (3) is that the relative wage changes of more and less educated natives are now much smaller, with the two groups experiencing more homogeneous (usually positive but not very significant) effects. This is because, while from 1990 to 2006 immigration led to rather unbalanced increases in labor supplies between workers with no high school degree (23.6%) and high school graduates (10%), increases were rather balanced between workers with high school or less (13%) and those with some college or more (10%). Hence, the value of $1/\sigma_{EDU,L}$ plays a fundamental role in determining the relative wage effects, and a value as large as 0.3 (column (1)) produces much larger effects relative to the preferred value of 0.03 used in columns (6)–(9). Indeed, in these specifications the negative effect on the least educated natives, due to the fact that the distribution of immigrants is tilted towards lower educational levels, is balanced, or more than balanced, by the positive effects, due to their imperfect substitutability. That is why even the least-educated natives face a small long-run positive effect of immigration. The wage loss of less-educated previous immigrants is between 4.8 and 8.1%. Increasing the value of $\sigma_{EDU,L}$ to infinity (which is never rejected in the estimates of Section 4.2.2) would only marginally change the estimated effect of immigrants on less educated natives.[34]

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34. The corresponding results are not reported but are available on request.

6. Conclusions

The present paper has extended the *national approach* to the analysis of the effect of immigration on wages in the tradition of Borjas (2003) and Borjas and Katz (2007). In particular, it has argued that a structural model of production, combining workers of different skills with capital, is necessary to assess the effect of immigration on the wages of native workers of different skills in the long run. Estimating a reduced-form or a partial elasticity does not give complete information about the total wage effect of immigration as these estimate only the effect of direct competition, whereas the total wage effect is also determined by indirect complementarities among different types of immigrants and natives. Using a nested-CES framework seems to be a promising way to make progress in understanding the total wage effect of immigration. And while such a framework imposes restrictions on cross-elasticities, it is flexible enough to allow for different nesting structures and, therefore, for testing alternative restrictions.

In this framework we found a small but significant degree of imperfect substitutability between natives and immigrants within education and experience groups. A substitution elasticity of around 20 is supported by our estimates. Allowing this elasticity to vary across education groups results in significantly lower estimates among less educated workers (around 11.1). In the long run, these estimates imply an overall average positive effect of immigration on native wages of about 0.6% and an overall average negative effect on the wages of previous immigrants of about −6%.

We have also argued that the elasticity of substitution between workers with no degree and workers with a high school degree is an important parameter in determining the wage effects of immigration. The established tradition in labor economics of assuming that this elasticity is large (around 33) is strongly supported by the data. Also consistent with the labor literature, we found that the elasticity of substitution between workers with some college education or more and those with a high school education or less is much smaller (around 2). The relatively balanced inflow of immigrants belonging to these two groups from 1990 to 2006 implies very small relative wage effects due to immigration. Varying the nesting or other elasticity assumptions (for example, by inverting education and experience in the nest, or allowing different elasticities of substitution between young and old workers) matter much less in determining the total wage effect of immigration on natives of different educational levels.

All in all, one finding seems robust: once imperfect substitutability between natives and immigrants is allowed for, over the period 1990–2006 immigration to the United States had at most a modest negative long-run effect on the real wages of the least educated natives. This effect is between −2.1% and +1.7% depending on the chosen nesting structure, with the positive results coming from the nesting structure preferred by the data. Our finding at the national level of a small wage effect of immigration on less-educated natives is in line with the findings identified at the city level.

Appendix A: Theory Appendix

A.1. Income Shares in the Nested CES

For parsimony it is useful to consider a situation in which workers' diversity is defined in terms of only one characteristic. This characteristic identifies groups that are numbered $d = 1, \ldots, D$. In this case, the CES labor aggregate in (1) can be defined as follows:

$$L = \left[\sum_{d=1}^{D} \theta_d \left(L_d \right)^{\frac{\sigma_D - 1}{\sigma_D}} \right]^{\frac{\sigma_D}{\sigma_D - 1}}, \tag{A.1}$$

where L_d is the number of workers in group d, θ_d is the relative productivity level of that group, and $\sigma_D > 0$ is the elasticity of substitution between any two groups. Productivity levels are standardized so that $\sum_d \theta_d = 1$.

   Given (A.1), the labor demand for workers in category d is

$$L_d = \frac{(w_d / \theta_d)^{-\sigma_D}}{\sum_d (w_d / \theta_d)^{1 - \sigma_D}} \sum_d w_d L_d, \tag{A.2}$$

so that the labor income share of workers with education d can be written as

$$s_d \equiv \frac{w_d L_d}{\sum_d w_d L_d} = \theta_d \frac{(w_d / \theta_d)^{1 - \sigma_D}}{\sum_d (w_d / \theta_d)^{1 - \sigma_D}}. \tag{A.3}$$

On the other hand, differentiation of (A.1) yields

$$\frac{dL}{dL_d} = \theta_d \left(\frac{L}{L_d} \right)^{\frac{1}{\sigma_D}}. \tag{A.4}$$

Then, (A.2), (A.3) and (A.4) together imply

$$\frac{d \ln L}{d \ln L_d} = \frac{dL}{dL_d} \frac{L_d}{L} = s_d.$$

A.2. Total Wage Effects of Immigration in Model B

We denote the change in the supply of foreign-born due to immigration between two Censuses in group $j(N)$ as $\Delta L_{F,j(N)} = L_{F,j(N),t+10} - L_{F,j(N),t}$. Then, we can use the demand functions (3) and take the total differential with respect to variation in all groups $j(N - 1)$ to derive the total effect of immigration on native and immigrant

wages. The resulting expressions are

$$
\left(\frac{\Delta w_{i(N-1)}^{D}}{w_{i(N-1)}^{D}}\right)^{\text{Total}} = \frac{1}{\sigma_{H-L}} \sum_{H-L} \sum_{\text{EDU}} \sum_{\text{EXP}} \left(s_{j(N-1),F}^{0} \frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)
$$

$$
+ \left(\frac{1}{\sigma_{\text{EDU},i}} - \frac{1}{\sigma_{H-L}}\right) \sum_{\text{EDU}} \sum_{\text{EXP}} \left(s_{j(N-1),F}^{1} \frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)
$$

$$
+ \left(\frac{1}{\sigma_{\text{EXP}}} - \frac{1}{\sigma_{\text{EDU},i}}\right) \sum_{\text{EXP}} \left(s_{j(N-1),F}^{2} \frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)
$$

$$
+ \left(\frac{1}{\sigma_N} - \frac{1}{\sigma_{\text{EXP}}}\right) \left(s_{j(N-1),F}^{3} \frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right) \tag{A.5}
$$

and

$$
\left(\frac{\Delta w_{i(N-1)}^{F}}{w_{i(N-1)}^{F}}\right)^{\text{Total}} = \frac{1}{\sigma_{H-L}} \sum_{H-L} \sum_{\text{EDU}} \sum_{\text{EXP}} \left(s_{j(N-1),F}^{0} \frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)
$$

$$
+ \left(\frac{1}{\sigma_{\text{EDU},i}} - \frac{1}{\sigma_{H-L}}\right) \sum_{\text{EDU}} \sum_{\text{EXP}} \left(s_{j(N-1),F}^{1} \frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)
$$

$$
+ \left(\frac{1}{\sigma_{\text{EXP}}} - \frac{1}{\sigma_{\text{EDU},i}}\right) \sum_{\text{EXP}} \left(s_{j(N-1),F}^{2} \frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)
$$

$$
+ \left(\frac{1}{\sigma_N} - \frac{1}{\sigma_{\text{EXP}}}\right) \left(s_{j(N-1),F}^{3} \frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right) - \frac{1}{\sigma_N} \frac{\Delta L_{F,i(N-1)}}{L_{F,i(N-1)}},
$$

$$
\tag{A.6}
$$

where $w_{i(N-1)}^{D}$ is the wage of domestic workers in group $i(N-1)$, $s_{j(N-1),F}^{m}$ is the share of labor income of foreign workers with characteristics $j(N-1)$ among all workers exhibiting the same characteristics up to m.

Using the percentage change in wages for each skill group, we can then aggregate and find the effect of immigration on several representative wages. The average wage for the whole economy in year t, inclusive of natives and immigrants, is given by

$$
\bar{w}_t = \sum_{H-L} \sum_{\text{EDU}} \sum_{\text{EXP}} \left(w_{i(N-1)}^{F} \varkappa_{i(N-1),F} + w_{i(N-1)}^{D} \varkappa_{i(N-1),D}\right),
$$

where $\varkappa_{i(N-1),F}$ ($\varkappa_{i(N-1),D}$) are the hours worked by immigrants (natives) in group $i(N-1)$ as a share of total hours worked in the economy. Similarly, the average wages of immigrants and natives can be expressed as weighted averages of individual group wages:

$$
\bar{w}_{Ft} = \frac{\displaystyle\sum_{H-L} \sum_{\text{EDU}} \sum_{\text{EXP}} \left(w_{i(N-1)}^{F} \varkappa_{i(N-1),F}\right)}{\displaystyle\sum_{H-L} \sum_{\text{EDU}} \sum_{\text{EXP}} \varkappa_{i(N-1),F}}
$$

and

$$\bar{w}_{Dt} = \frac{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \left(w^D_{i(N-1)} \varkappa_{i(N-1),D} \right)}{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \varkappa_{i(N-1),D}}.$$

The percentage change in the average wage of natives as a consequence of changes in each group's wage due to immigration is given by

$$\frac{\Delta \bar{w}_{Dt}}{\bar{w}_{Dt}} = \frac{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \left(\frac{\Delta w^D_{i(N-1)}}{w^D_{i(N-1)}} \frac{w^D_{i(N-1)}}{\bar{w}_{Dt}} \varkappa_{i(N-1),D} \right)}{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \varkappa_{i(N-1),D}}$$

$$= \frac{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \left(\frac{\Delta w^D_{i(N-1)}}{w^D_{i(N-1)}} \right) s^0_{j(N-1),D}}{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} s^0_{j(N-1),D}}, \tag{A.7}$$

where $\Delta w^D_{i(N-1)}/w^D_{i(N-1)}$ represents the percentage change in the wage of US-born in group $i(N-1)$ due to immigration, and its expression is given in (A5). Similarly, the percentage change in the average wage of foreign-born workers is

$$\frac{\Delta \bar{w}_{Ft}}{\bar{w}_{Ft}} = \frac{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \left(\frac{\Delta w^F_{i(N-1)}}{w^F_{i(N-1)}} \frac{w^F_{i(N-1)}}{\bar{w}_{Ft}} \varkappa_{i(N-1),F} \right)}{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \varkappa_{i(N-1),F}}$$

$$= \frac{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \left(\frac{\Delta w^F_{i(N-1)}}{w^F_{i(N-1)}} \right) s^0_{j(N-1),F}}{\sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} s^0_{j(N-1),F}}, \tag{A.8}$$

where $\Delta w^F_{i(N-1)}/w^F_{i(N-1)}$ represents the percentage change in the wage of foreign-born workers in group $i(N-1)$ due to immigration, and its expression is given in (A.6). Finally, by aggregating the total effect of immigration on the wages of all groups, native and foreign, we can obtain the effect of immigration on average wages:

$$\frac{\Delta \bar{w}_t}{\bar{w}_t} = \sum\limits_{H-L} \sum\limits_{\text{EDU}} \sum\limits_{\text{EXP}} \left(\frac{\Delta w^F_{i(N-1)}}{w^F_{i(N-1)}} s^0_{j(N-1),F} + \frac{\Delta w^D_{i(N-1)}}{w^D_{i(N-1)}} s^0_{j(N-1),D} \right). \tag{A.9}$$

Recall that the variables $s^0_{j(N-1),F}$ and $s^0_{j(N-1),D}$ represent the group's share in total wages and, as shown in Section A.1, in the nested-CES framework the correct weights in order to obtain the percentage change in average wages are the shares in the wage bill and not the shares in employment. We adopt the same averaging procedure (weighting percentage changes by wage shares) in calculating the effects of immigration on specific groups of US- and foreign-born workers.

Appendix B: Data Appendix

B.1. IPUMS Census Data

We downloaded the IPUMS data on 1 June 2008. The data originate from these samples: 1960, 1% sample of the Census; 1970, 1% sample of the Census; 1980, 5% sample of the Census; 1990, 5% sample of the Census; 2000, 5% sample of the Census; 2006, 1% sample of the ACS. We constructed two datasets that cover slightly different samples. The first aggregates the employment and hours worked by US- and foreign-born males and females in 32 education–experience groups in each Census year. This is called the *employment sample*. The second is called the *wage sample* and is used to calculate the average weekly and hourly wages for US- and foreign-born males and females in the same 32 education–experience groups in each Census year. The first sample is slightly more inclusive than the second.

B.2. IPUMS–CPS Data

We downloaded the IPUMS–CPS data on 28 April 2008, including the years 1963 to 2006 in the extraction. As for the Census data, we constructed an *employment sample* and a *wage sample*. We used the first sample to calculate measures of hours worked and employment, and the second sample to calculate the average weekly wages for US- and foreign-born males and females in each skill group and in each Census year. The first sample is more inclusive than the second. We constructed hours worked, employment and the average wage for each of 4 education groups (workers with no high school, high school graduates, workers with some college, college graduates), following as closely as possible the procedure described in Katz and Murphy (1992), pp. 67–68.

Further details on the definitions of samples and variables that allow the exact reproduction of the sample and results of this paper can be found in the online appendix to the present paper.

Appendices C–G are available online.

References

Acemoglu, Daron (2002). "Directed Technical Change." *Review of Economic Studies*, 69, 781–810.
Angrist, Joshua (1995). "The Economic Returns to Schooling in the West Bank and Gaza Strip." *American Economic Review*, 85, 1065–1087.
Autor, David, Lawrence Katz, and Alan Krueger (1998). "Computing Inequality: Have Computers Changed The Labor Market?" *The Quarterly Journal of Economics*, 113, 1169–1213.
Borjas, George, Richard Freeman, and Larry Katz (1997). "How Much Do Immigration and Trade Affect Labor Market Outcomes?" *Brookings Papers on Economic Activity*, 1997(1), 1–90.
Borjas, George (2003). "The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market" *Quarterly Journal of Economics*, 118, 1335–1374.

Borjas, George (2006). "Native Internal Migration and the Labor Market Impact of Immigration." *Journal of Human Resources*, 41, 221–258.

Borjas, George, and Lawrence Katz (2007). "The Evolution of the Mexican-Born Workforce in the United States." In *Mexican Immigration to the United States*, edited by George Borjas .National Bureau of Economic Research Conference Report, Cambridge, MA.

Borjas, George, Jeffrey Grogger, and Gordon Hanson (2008). "Imperfect Substitution between Immigrants and Natives: A Reappraisal." National Bureau of Economic Research, Working Paper # 13887, Cambridge, MA.

Card, David, and Thomas Lemieux (2001). "Can Falling Supply Explain the Rising Returns to College for Younger Men? A Cohort Based Analysis." *Quarterly Journal of Economics*, 116, 705–746.

Card, David (2001). "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics*, 19, 22–64.

Card, David (2007). "How Immigration Affects U.S. Cities." CReAM Discussion Paper, no. 11/07, University College London.

Card, David, and Ethan Lewis (2007). "The Diffusion of Mexican Immigrants During the 1990s: Explanations and Impacts." In *Mexican Immigration to the United States*, edited by George Borjas. National Bureau of Economic Research Conference Report, Cambridge, MA.

Caselli, Francesco and Wilbur Coleman (2006). "The World Technology Frontier." *American Economic Review*, 96, 499–522.

Cortes, Patricia (2008). "The Effect of Low-skilled Immigration on US Prices: Evidence from CPI Data." *Journal of Political Economy*, 116, 381–422.

D'Amuri, Francesco, Gianmarco Ottaviano, and Giovanni Peri (2010) "The Labor Market Impact of Immigration in Western Germany in the 1990s." *European Economic Review*, 54, 550–570.

Dustamnn Christian, Tommaso Frattini and Ian Preston (2008) "The Effect of Immigration along the Distribution of Wages." CReAM Discussion Paper 0803, University College London.

Friedberg, Rachel, and Jennifer Hunt (1995). "The Impact of Immigrants on Host Country Wages, Employment and Growth." *Journal of Economic Perspectives*, 9, 23–44.

Friedberg, Rachel (2001). "The Impact of Mass Migration on the Israeli Labor Market." *Quarterly Journal of Economics*, 116, 1373–1408.

Goldin, Claudia and Larry Katz (2008). "The Race Between Education and Technology." Harvard University Press, Cambridge, MA.

Gollin, Douglas (2002). "Getting Income Shares Right." *Journal of Political Economy*, 100, 458–474.

Jaeger, David (1996). "Skill Differences and the Effect of Immigrants on the Wages of Natives." U.S. Bureau of Labor Statistics, Economic Working Paper #273. Washington, DC.

Johnson, George E., (1997). "Changes in Earnings Inequality: The Role of Demand Shifts." *The Journal of Economic Perspectives*, 11, 41–54.

Jones, Charles (2005). "The Shape of Production Functions and the Direction of Technical Change." *Quarterly Journal of Economics*, 120, 517–549.

Kaldor, Nicholas (1961). "Capital Accumulation and Economic Growth." In *The Theory of Capital*, edited by F. A. Lutz and D. C. Hague. St. Martins, New York.

Katz, Larry and Kevin Murphy (1992). "Changes in Relative Wages 1963–1987: Supply and Demand Factors." *Quarterly Journal of Economics*, 107, 35–78.

King, Miriam, Steven Ruggles, Trent Alexander, Donna Leicach, and Matthew Sobek (2009). Integrated Public Use Microdata Series, Current Population Survey: Version 2.0. [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], http://www.ipums.org.

Krusell, Per, Lee Ohanian, Victor Rios-Rull, and Giovanni Violante (2000). Capital–Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica*, 68, 1029–1053.

Lewis, Ethan (2005). "Immigration, Skill Mix, and the Choice of Technique." Federal Reserve Bank of Philadelphia Working Paper no. 05-08.

Longhi, Simonetta, Peter Nijkamp, and Jacques Poot (2005). "A Meta-Analytic Assessment of the Effect of Immigration on Wages." *Journal of Economic Surveys*, 86, 451–477.

Manacorda Marco, Alan Manning, and John Wadsworth (Forthcoming). "The Impact of Immigration on the Structure of Wages: Theory and Evidence from Britain." *Journal of European Economic Association*, this issue.

Murphy, Kevin and Finis Welch (1992). "The Structure of Wages." *The Quarterly Journal of Economics*, 107, 285–326.

National Research Council (1997). "The New Americans: Economic, Demographic, and Fiscal Effects of Immigration." National Academy Press, Washington, DC.

Ottaviano, Gianmarco, and Giovanni Peri (2005). "Cities and Cultures." *Journal of Urban Economics*, 58, 304–307.

Ottaviano, Gianmarco, and Giovanni Peri (2006a) "Rethinking the Effect of Immigration on Wages" National Bureau of Economic Research, Working Paper # 12496, Cambridge, MA.

Ottaviano, Gianmarco, and Giovanni Peri (2006b). "The Economic Value of Cultural Diversity: Evidence from U.S. Cities." *Journal of Economic Geography*, 6, 9–44.

Ottaviano, Gianmarco, and Giovanni Peri (2008). "Immigration and National Wages: Clarifying the Theory and the Empirics." National Bureau of Economic Research Working Papers # 14188, Cambridge, MA.

Peri, Giovanni and Chad Sparber (2009). "Task Specialization, Immigration, and Wages." *American Economic Journal: Applied Economics, American Economic Association*, 1, 135–169.

Ramsey, Frank (1928). "A Mathematical Theory of Saving." *Economic Journal*, 38, 543–559.

Raphael Steven and Ed Smolensky (2008). "Immigration and Poverty in the Unites States." Working paper, UC Berkeley, April 2008.

Ruggles, Steven, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander (2009) Integrated Public Use Microdata Series: Version 4.0 [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], http://www.ipums.org.

Solow, Robert (1956). "A Contribution to the Theory of Economic Growth." *Quarterly Journal of Economics*, 70, 65–94.

Welch, Finis (1979). "Effects of Cohort Size on Earnings: The Baby Boom Babies Financial Boost." *Journal of Political Economy*, 87, 65–97.