Rethinking the Effect of Immigration on Wages

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Abstract

This paper calculates the effects of immigration on the wages of native U.S. 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 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, a small but significant degree of imperfect substitutability between natives and immigrants and the other estimated elasticities imply that in the period from 1990 to 2006 immigration had a very small effect on the wages of native workers with no high school degree (between −0.1% and +0.6%). It also had a small positive effect on average native wages (+0.6%) and a substantial negative effect (−6%) on wages of previous immigrants in the long run.

Key Words: Native-Immigrant Complementarities, Skills, Partial and Total wage effects, National Approach.

JEL Codes: F22, J61, J31.

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1 Introduction

For a long time the empirical analysis of cross-city and cross-state evidence in the U.S. 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 immigration effects using national level data and found a significant negative effect of immigration on the wages of natives with no high school diploma.[2] These studies have argued that wages across local labor markets are subject to the equalizing pressure coming from the spatial arbitrage of mobile workers. As a result, the wage effects of immigration are better detectable at the national level by exploiting the variation of 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 U.S. worker to react to local immigration by changing residence within the US it is much harder for her to do so by relocating across the U.S. border or by changing her own skill mix. Accordingly, the estimation of the substitutability among workers with different skills should play center stage 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, differently from 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 native 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. And the answer to this question has important implications as the degree of imperfect substitutability affects the impact of immigrants on the wage of natives with similar skills.

Some recent papers have also estimated the native-immigrant elasticity of substitution. Card (2009) using U.S. city data for year 2000, Raphael and Smolensky (2008) using U.S. data 1970-2005, Manacorda et al. (2008) using UK data, and D'Amuri et al. (forthcoming) 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.[3] On the other hand, Borjas, Grogger and Hanson (2008) show that one can get small and insignificant estimates for that inverse elasticity and therefore they find no evidence of imperfect substitutability

[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).

[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, pages 468-469, for a discussion of this issue). Until very recently, however, only very few studies have directly estimated the elasticity of substitution between natives and immigrants. Jaeger (1996) only covers metropolitan areas 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.

in specifications 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, as the inflow of immigrants to the U.S. in the last 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) who 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 the wages of high school drop outs 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 size 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 such 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 U.S. Census data only consists of 192 skill by year observations on employment and wages. Adding structure, like the nested-CES labor composite we introduce below, allows the 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

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

[5] See, e.g., 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), page 68, and Goldin and Katz (2008) and also Figure 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.

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 that together span most of the structures used to estimate the substitutability among skill groups in the existing literature. These four nesting models are depicted in Figure 1. Model A augments the structure proposed by Borjas (2003, Section VII) by nesting two additional groups of US- and Foreign-born workers[8] into each of the original eight experience groups (five year intervals from 0 to 40 years of experience), which are themselves nested into the four original education groups (No Degree, High School Graduates, Some College and College Graduates). 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 in 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).[9] This alternative partition is considered in model B in which "No Degree" and "High School Graduates" are nested into a Low Education group, whereas "Some College" and "College Graduates" are nested into a High Education group, allowing workers' substitutability to differ within and between these two broader groups. Models C and D cover plausible alternatives that are not much used by the existing literature. Model C allows for a two-stage nest of experience levels where two broader groups, Young (1 to 20 years of experience) and Old (21 to 40 years of experience) nest four five-year experience groups each. Workers' substitutability is allowed to be different within and between the two broader groups. Finally, in model D the nesting order of education and experience 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.[10]

While overall the elasticity estimates and, therefore, the computed wage effects are somewhat sensitive to model specification, some results are robust across specifications. First, we find a small but significant degree

[8] Indicated in Figure 1 as D, for domestic, and F, for foreign.

[9] See, e.g., 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.

[10] 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.

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 -2.3% to -3.1% over the period 1990-2006. This model would imply a wage loss of less educated natives of -4.1% when the elasticity of substitution native-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 quarter. This imperfect substitutability also implies that, on average, immigrants already in the U.S. suffer much larger wage losses than natives as a consequence of new immigrants. Based on model A, their average wage losses due to immigration are calculated around 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 very small and in several specifications even positive (between -0.1% and 0.6%). The reason for this result is the rather balanced inflow of immigrants between the broad High Education and Low Education groups together with the imperfect substitutability between natives and immigrants.

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 organize 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), Ottaviano and Peri (2005, 2006b) and Peri (2009)[11]. 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.[12]

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, e.g., Katz and Murphy 1992; Card and Lemieux 2001; Borjas, 2003; Borjas and Katz, 2007). This is based on an aggregate production function that parametrizes 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 below), 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, and 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).[13] 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 $\alpha A\left(K/L\right)^{1-\alpha}$ units of aggregate output.

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

[11] Our method would also miss any potential aggregate negative productivity effect of immigration.

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

[13] The Cobb-Douglas functional form implies that physical capital has the same degree of substitutability with each type of workers. Some influential studies (e.g. Krusell et al. 2001) have argued that physical capital complements highly educated 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 U.S. over the period considered.

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. Also this implication is supported by the data, as the real return to capital and the capital-output ratio in the U.S. do not exhibit any trend in the long run while the capital-labor ratio grows at a constant rate. This is shown in Figures 2 and 3 for the period 1960-2004: both the capital-output ratio and the de-trended 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 Workers' Heterogeneity in a CES Model: Basic Results

As workers are heterogeneous, the zero effect of immigration on the average wage at the aggregate level 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 terms, these effects on wages should depend on how substitutable are workers of different types and how large is the inflow of workers of each type.

To illustrate this intuition we first consider a situation in which workers' diversity is defined in terms of only one characteristic. This characteristic identifies groups that are numbered $d = 1, ..., D$ and the heterogeneity across groups has a very symmetric representation, as implied by a constant and common elasticity between any two groups. In this case, the CES labor aggregate in (1) can be defined as follows:

$$L = \left[\sum_{d=1}^{D} \theta_d \left(L_d \right)^{\frac{\sigma_D - 1}{\sigma_D}} \right]^{\frac{\sigma_D}{\sigma_D - 1}} \tag{2}$$

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 $\sum_d \theta_d = 1$ and any common multiplying factor is absorbed in the TFP parameter A of (1). Both A and θ_d depend on exogenous technological factors only.

Under perfect competition, profit maximization implies that the (logarithmic) real wage of a worker in group d is determined by the (logarithmic) value of her marginal productivity

$$\ln(w_d) = \ln(\alpha A \kappa^{1-\alpha}) + \frac{1}{\sigma_D} \ln(L) + \ln \theta_d - \frac{1}{\sigma_D} \ln \left(L_d \right) \tag{3}$$

where κ is the time dependent exogenous capital-labor ratio along the balanced growth path and aggregate output has been taken as numeraire. Expression (3) reveals two key properties of the CES-nested approach. First, it provides the empirical basis to estimate the parameter $1/\sigma_D$. In particular, having several observations over time for wage and employment of each group, one can regress the logarithmic wage of group d on its logarithmic labor supply L_d to obtain $-1/\sigma_D$. Expression (3) implies that the regression should include time fixed effects to control for the variation of the aggregate terms $\ln(\alpha A \kappa^{1-\alpha})$ and $\ln(L)$ and group fixed effects to control for the the relative efficiency $\ln \theta_d$. Second, the impact of a change in the supply of a specific group of workers L_i on the wage of a different group of workers L_j depends only on the change in the common CES aggregator L. This property allows one to compute the percentage (logarithmic) change in the wage of a group w_i due to a percentage change in the labor supply of a different group L_j once the elasticity σ_D is known (estimated) using the following formula:

$$\frac{\Delta w_i/w_i}{\Delta L_j/L_j} = \frac{1}{\sigma_D}\frac{\Delta L/L}{\Delta L_j/L_j} = \frac{s_j}{\sigma_D} > 0 \tag{4}$$

where $s_j \in (0,1)$ denotes the share of group j in aggregate labor income: $s_j \equiv w_j L_j / \sum_{d=1}^{D} w_d L_d$. Analogously, the percentage wage impact due to a change of workers in the same group can be computed as:[14]

$$\frac{\Delta w_j/w_j}{\Delta L_j/L_j} = \frac{s_j}{\sigma_D} - \frac{1}{\sigma_D} < 0 \tag{5}$$

These expressions show that, as argued above, immigrants put downward pressure on the wages of workers with similar characteristics and upward pressure on the wages of workers with different characteristics. Note that both (4) and (5) contain only the elasticity σ_D and the observable share s_j.

2.3 Wage Effects in a Flexible Nested-CES Model

The simple and symmetric CES model presented above is, however, not good enough to capture the actual heterogeneity of workers. Workers' heterogeneity involves more than one characteristic (education and experience are typical ones). Differences in one characteristic may affect the cross-group elasticity of substitution more than differences in another and groups that differ in a characteristic need not be symmetric in their substitutability with each other. The results (3), (4) and (5) can be readily generalized to situations in which workers differ by an arbitrary number of characteristics and the elasticity of substitution between workers depends on them sharing different sets of those characteristics.

Consider $N+1$ characteristics numbered $n = 0, ..., N$. Characteristic 0 is common to all workers and defines them as such. We first partition workers into groups $i_1 = 1, ..., M_1$ that differ according to characteristic 1.

[14] See Appendix A.1 for details on the derivation.

Then, each of these groups is itself partitioned into groups $i_2 = 1, ..., M_2$ that differ according to characteristic 2, and so on up to characteristic N. This sequential partitioning and its relative notation is illustrated in Figure 4. The index $n = 0, ..., N$ 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 index also 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:

$$L_{i(n)} = \left[\sum_{i(n+1)\in i(n)} \theta_{i(n+1)} \left(L_{i(n+1)}\right)^{\frac{\sigma_{n+1}-1}{\sigma_{n+1}}} \right]^{\frac{\sigma_{n+1}}{\sigma_{n+1}-1}}, \; n = 0, .., N \tag{6}$$

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 $\sigma_n > 0$ is the elasticity of substitution between types $i(n)$. The fact that the sequential partitioning of workers leads to less and less heterogeneous groups $i(n)$ as n increases can be captured by assuming that $\sigma_{n+1} > \sigma_n$. Since type $i(0)$ includes all workers, we can embed the nested structure defined by (6) in (1) by imposing $L = L_{i(0)}$.

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

$$\ln(w_{i(N)}) = \ln(\alpha A \kappa^{1-\alpha}) + \frac{1}{\sigma_1}\ln(L) + \sum_{n=1}^{N} \ln \theta_{i(n)} - \sum_{n=1}^{N-1} \left(\frac{1}{\sigma_n} - \frac{1}{\sigma_{n+1}} \right) \ln\left(L_{i(n)}\right) - \frac{1}{\sigma_N} \ln\left(L_{i(N)}\right) \tag{7}$$

This expression holds for $N > 2$ with the case of $N = 1$ still covered by (3). This expression can be used as the empirical basis for estimating the substitutability parameters σ_n with $n = 1, ..., N$. 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 (7) implies:

$$\ln\left(\frac{w_{i(N)}}{w_{j(N)}}\right) = \ln\frac{\theta_{i(n)}}{\theta_{j(n)}} - \frac{1}{\sigma_N} \ln\left(\frac{L_{i(N)}}{L_{j(N)}}\right) \tag{8}$$

Therefore, $-1/\sigma_N$ can be estimated from observations on wages and employment levels over time, using fixed type effects to control for $\ln\left(\theta_{i(n)}/\theta_{j(n)}\right)$. Second, for any other nesting level $m = 1, ..., N - 1$, 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 to N in (7) 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 $\sum_{n=1}^{m-1} (1/\sigma_n - 1/\sigma_{n+1}) \ln \left(L_{i(n)}\right)$ that do not change with characteristic m.

Mirroring the simple case with a single differentiating characteristic, once used to estimate the elasticities of substitution between different types of workers, the wage equation (7) can also be exploited 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 define $s^n_{i(N)}$ to denote type $i(N)$'s share of the labor income among workers exhibiting the same characteristics up to n as that type. Hence, $s^{n-1}_{i(N)} \leq s^n_{i(N)}$ and $s^N_{i(N)} = 1$. 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 $j(N)$ sharing with them characteristics up to m as

$$\frac{\Delta w^0_{j(N)}/w^0_{j(N)}}{\Delta L_{i(N)}/L_{i(N)}} = \frac{s^0_{i(N)}}{\sigma_1} > 0, \quad m = 0 \tag{9}$$

and

$$\frac{\Delta w^m_{j(N)}/w^m_{j(N)}}{\Delta L_{i(N)}/L_{i(N)}} = -\sum_{n=0}^{m-1} \frac{s^{n+1}_{i(N)} - s^n_{i(N)}}{\sigma_{n+1}} < 0, \quad m = 1, ..., N \tag{10}$$

Results (9) and (10) embed (4) and (5) as special cases when there is only one differentiating characteristic with $m = 0$ and $m = 1$ respectively. Two remarks on (9) and (10) 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 depressing effect is stronger the larger the number of differentiating characteristics $j(N)$ has in common with $i(N)$. Both results depend on having nested the characteristics so that $\sigma_{n+1} > \sigma_n$.

2.4 Description of Alternative Nesting Structures

The traditional characteristics used in the literature to partition heterogeneous workers are education and experience (see, e.g., 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 because, even considering workers with equivalent education and experience, natives and immigrants differ in several respects that are relevant to the labor market. First, people that 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 (e.g., cooking, crafting, opera singing, soccer playing) and limits (e.g., limited knowledge of the language or culture of the host country), which create comparative advantages in some tasks and comparative disadvantages in others.[15] Third, due to comparative advantages, migration networks or historical accidents,

[15] See Peri and Sparber (2009) for evidence supporting the existence of different comparative advantages in production tasks

immigrants tend to choose different occupations than 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.[16] 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 N-th 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 1 as specific cases of the flexible nested-CES model presented in Section 2.3. Model A builds on Borjas (2003) and Borjas and Katz (2007). Using the notation introduced in Section 2, 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 = ("0-5", "6-10", "11-15", "16-20", "21-25", "26-30", "31-35", "36-40" years); and 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[17] Accordingly, in model B workers are first partitioned in terms of two broad educational characteristics, each of which comprising 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"), then narrowly defined education is characteristic 2 with i_2 =("No Degree" and "High School Degree") partitioning "Low Education" and i_2 = ("Some College Education" and "College Degree") partitioning "High Education". Experience is characteristic 3 still partitioned in 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, being smaller for groups that are closer in terms of experience. We again have $N = 4$ but there is only one level of educational characteristics with its 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" and "16-20"within the group "$Young$" and i_3="21-25", "26-30", "31-35", and "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 which imply

between US- and foreign-born workers.

[16] 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.

[17] See Goldin and Katz (2008), Katz and Murphy (1992), Autor Katz and Krueger (1997), Krusell et al. (2000), Card and Lemieux (2001), Acemoglu (2002) and Caselli and Coleman (2006) among others.

that the elasticity of substitution across education groups is generally smaller than across experience groups. If, however, workers of different education level 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 and 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 last category so that $N = 3$.

2.5 Partial and Total Wage effects of Immigration

The flexible nested-CES model of Section 2.3 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 impacts of immigration in all other groups of workers. This implies that the total wage effects on natives across groups depend on the relative size 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 N-th characteristic of 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 *direct partial wage effect* of immigration the wage impact on native workers of 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.[18] The direct partial wage effect has been 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 $n = 1, ..., N-1$). In terms of our flexible model, the resulting partial elasticity can be written as:

$$\varepsilon_{i(N)}^{N-1} = -\left(\frac{1}{\sigma_{N-1}} - \frac{1}{\sigma_N}\right) s_{i(N)}^{N-1} \tag{11}$$

Note, however, that the direct partial wage effect (11) coincides only with the last among the several terms composing the summation in (10) as this includes both direct and indirect partial 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

[18] For instance, in Borjas (2003, section 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.

through the term $-\left(1/\sigma_{N-1} - 1/\sigma_N\right)\ln\left(L_{i(N-1)}\right)$ in (7).

Hence, two important observations on (11) 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 (i.e. $\sigma_N > \sigma_{N-1}$). Second, the value and the sign of $\varepsilon_{i(N)}^{N-1}$, however, give incomplete information about the overall effect of immigrant supply changes on the wages of domestic workers. Indeed, (11) includes only the last term of (10), 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 (10) across all the $i(N)$'s 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. 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's with the income shares $s_{i(N)}^n$'s in (10) 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 be computed only by combining *own*-group effects with the set of *cross*-group effects. In Section 5 we will show how misleading it can be to use the direct partial wage effects to infer the total wage effects of immigration.

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).[19] The data we use are downloaded from the integrated public use microdata samples (IPUMS) where the original sources are the U.S. 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

[19] For further details see Appendix B and the companion technical appendix available on-line (called On-line Appendix). Together with exhaustive information on data, variable definitions and sample selection, the on-line appendix also provides the files and codes needed to reproduce all the results in this paper.

under the assumption that people without 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 1 to 5 years of experience and ending with those with 36 to 40 years of experience[20]. The status of "foreign-born" is given to those workers who are non-citizens 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 (i.e., 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 work-week.[21] 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 described above 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 and 2006). They also allow us to construct the wage bill share of each group and sub-group. 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 school graduates and the group of workers

[20] Workers with 0 years of potential experience or less and with more than forty years of potential experience are dropped from the sample.

[21] This sample excludes workers with low "labor market attachment" who could be different from full-time workers and whose average weekly wage can introduce non-classical measurement error, as argued by Borjas, Grogger and Hanson (2008).

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 2.4. 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[22]. 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). It is, therefore, 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 2.4, in all our nesting models the place of birth is the N-th 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 (8) for all models through the following common empirical specification:

$$\ln\left(\frac{w_{F,k,t}}{w_{D,k,t}}\right) = \phi_k + \phi_t - \frac{1}{\sigma_N}\ln\left(\frac{L_{F,k,t}}{L_{D,k,t}}\right) + u_{it} \qquad (12)$$

where $w_{D,k,t}$ and $w_{F,k,t}$ 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. $L_{D,k,t}$ and $L_{F,k,t}$ are the corresponding hours worked

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

(or employment). Expression (12) assumes that relative productivity $\ln(\theta_{F,k,t}/\theta_{D,k,t})$ in skill group k can be represented as $\phi_k + \phi_t + u_{it}$ where ϕ_k is a set of 32 education-experience effects, ϕ_t is a set of 6 year effects and u_{it} are zero-mean random variables uncorrelated with relative labor supply $\ln(L_{F,k,t}/L_{D,k,t})$ (more on this below). 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 variation over time ϕ_t across groups, due for instance to change in immigration policies. We also assume that their remaining time variations u_{it} are independent of relative labor supply. While imposing specific restrictions on the behavior of relative productivity, the foregoing assumptions seem reasonable. First, as 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) 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[23].

Before commenting on the regression results reported in Tables 2, it is useful to have a preliminary look at the data. Figure 5 shows the scatterplot of $\ln(w_{F,k,t}/w_{D,k,t})$ versus $\ln(L_{F,k,t}/L_{D,k,t})$ and the corresponding regression line from a simple OLS estimation including all 32 education-experience groups in all considered years. 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 considered 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 reporting the values of $-1/\sigma_N$ estimated through (12). Each entry in the table corresponds to an estimate from a different regression. Columns 1 and 4 report the estimates obtained without including the fixed effects ϕ_k and ϕ_t in the regression, while other columns always include them. The corresponding method of estimation is least squares, weighting each cell by the size of its labor supply. In Columns 3 and 6, instead, we use OLS without weighting the cells. The reported standard errors are heteroskedasticity-robust and clustered over skill-groups to allow error correlation within group. 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

[23] 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.

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 worked hours, as measure of relative labor supply.

Two results emerge clearly from the first four rows of estimates in 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%. 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 (60's) or the most recent one (2000-2006), clustering the standard errors over education groups (or experience groups) only, 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 productivities have to be uncorrelated with relative labor supplies after controlling for the fixed effects. Immigrant-biased productivity shocks concentrated in some cells, however, may attract more immigrants to those cells, thus inducing a positive correlation between relative productivities and labor supplies. 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 implied by our estimates. To control for some systematic types of correlation of the error with the explanatory variable over time and across groups, one can include additional specific effects. Borjas, Grogger and Hanson (2008) in a specification otherwise similar to (12) 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 fixed effects. This reduces the point estimates and increases the standard errors, which become mostly larger than 0.03 and often as large as 0.04 (especially in the male and pooled sample), posing problems in identifying a coefficient $-1/\sigma_N$ mostly estimated in the neighborhood of -0.05. Based on this results, Borjas, Grogger and Hanson (2008) conclude that there is no compelling evidence of imperfect substitutability. However, given their standard errors, they can rarely reject values of $-1/\sigma_N$ of -0.05. Also there is no theoretical reason to include those extra effects and using such a large number of fixed effects is rarely done in the literature when estimating the elasticities of substitution between different education or experience groups. Hence it seems fair to conclude that a small but significant degree of imperfect substitutability between natives and immigrants is supported by the data.[24]

[24] Other recent studies have estimated $-1/\sigma_N$ for other countries using specifications similar to (12). For Germany D'Amuri et al. (forthcoming) find values around -0.05, significantly different from 0. For the UK, Manacorda et al. (2008) find values mostly

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 as such immigrants tend to have less English language skills. As they have instead 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, as the difference in skills tends to decrease the longer immigrants stay in the U.S., 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 Rows 5 to 8 show the estimates of $-1/\sigma_N$ when we restrict the sample to cells including alternatively workers with no degree (Row 5) high school degree (Row 6), some college education (Row 7) or college degree (Row 8). 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 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. Rows 9 to 12 show 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), 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 observe also 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 native 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 (12) 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, $\widehat{\theta}_{F,k} = \exp(\widehat{\phi_k})/(1+\exp(\widehat{\phi_k}))$ and $\widehat{\theta}_{D,k} = 1/(1+\exp(\widehat{\phi_k}))$ respectively, which can be used to construct the labor composite $L_{i(N-1)}$ for group $i(N-1)$ using formula (6) for $n = N-1$.[25] We can then

between -0.15 and -0.20, also significantly different from 0.

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

calculate the corresponding average wage $w_{i(N-1)}$ and estimate $-1/\sigma_{N-1}$ by implementing equation (7). 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 $\sum_{n=1}^{N-2}(1/\sigma_n - 1/\sigma_{n+1})\ln\left(L_{i(n)}\right)$. The second controls for the systematic variation of group specific productivities $\ln\theta_{i(N-1)}$.

The first type of fixed effects is dictated by the nested-CES structure and, therefore, depend 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 on which specific effects to include in order to control for such correlation, we simply assume that, while $\ln\theta_{i(N-1)}$ may have a systematic component across groups 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 $L_{i(N-1)}$, eventually adding 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 (7) to level $n-1$.

Let us emphasize that, while we estimate the elasticity σ_{N-1} (and higher level elasticities σ_n with $n = 1, ..., N-2$) by implementing (7), but 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 extremely useful 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 (7) and including 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; 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); σ_{H-L} and σ_{EDU} have been estimated by Katz and Murphy

[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 are captured by education-by-time effects.

(1992) and Goldin and Katz (2008). This means 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 few large labor aggregates for which the census data provide very few observations through time (6 year points only). For this reason, we complement the estimates using 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 $-1/\sigma_{EXP}$ and $-1/\sigma_{Y-O}$ obtained for the different nesting structures by implementing the appropriate versions of equation (7). All regressions are estimated using 2SLS and immigrant labor supply to instrument total labor supply (measured as 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 $-1/\sigma_{EXP}$, models A and B generate exactly the same regression equation for which estimates are reported in Column 1. Model C produces estimates of $-1/\sigma_{EXP}$ at level $N-1$ and of $-1/\sigma_{Y-O}$ at level $N-2$. These are in Columns 2 and 3 respectively. Model D generate estimates of $-1/\sigma_{EXP}$ 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 women wage sample 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 women wage sample 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, e.g., 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 $-1/\sigma_{EXP}$ 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 to 35 years of experience). Finally, in the most influential

[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 assumption is the common one in the literature on the national wage effect of immigrants.

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 $\sigma_{EXP} = 5$.

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 $-1/\sigma_{EXP}$ 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 $1/\sigma_{Y-O} = 1/\sigma_{EXP}$ model C reduces to model A and no previous study has found $1/\sigma_{Y-O}$ different from $1/\sigma_{EXP}$, we interpret the foregoing 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 $-1/\sigma_{EDU}$ reporting the estimates obtained from the appropriate versions of (7) 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) as 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 as considering high school graduates or less as Low Education workers and college educated or more as High

[28] We have also estimated $-1/\sigma_{Y-O}$ and $-1/\sigma_{EXP}$ on yearly CPS data, using a method similar to Katz and Murphy (1992). This is reported in our on-line appendix. 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 $-1/\sigma_{EXP}$ are mostly between -0.1 and -0.2.

Education workers leaves us with only 12 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 (7) for model B at the highest level of nesting ($n = 1$) for $i(1)$=High and $i(1)$=Low and taking the ratio between the resulting expressions, we obtain:

$$\ln\left(\frac{w_{H,t}}{w_{L,t}}\right) = \ln\frac{\theta_{H,t}}{\theta_{L,t}} - \frac{1}{\sigma_{H-L}}\ln\left(\frac{L_{H,t}}{L_{L,t}}\right) \tag{13}$$

where $w_{H,t}$ is the average weekly wage of workers with college degree or more (calculated as hours-weighted average) and $w_{L,t}$ is the hours-weighted average weekly wage of high school graduates or less. The parameters $\theta_{H,t}$ and $\theta_{L,t}$ capture the productivities of the two groups and $L_{H,t}$ and $L_{L,t}$ measures their labor supplies. Note that equation (13) is identical to the one estimated by Katz and Murphy (1992) (henceforth, simply KM).

We implement (13) 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 $\ln(\theta_{H,t}/\theta_{L,t})$ 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 $L_{H,t}$ and $L_{L,t}$ 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 $L_{H,t}$ and partly to $L_{L,t}$ according to some regression weights. In our case, instead, all workers with some college education are included in $L_{H,t}$.

The estimates of $-1/\sigma_{H-L}$ based on (13) are reported in Column 1 of Table 5. As 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). Row 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 of them in the former group as implied by our model. In addition, Row 3 uses employment rather than hours worked as measure of labor supply while Row 4 omits the 60s. 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

[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 C and, in greater details, in the on-line appendix to this paper.

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 (13) is also useful to estimate the elasticities of substitution between narrow education categories within the High and Low Education groups. In particular, in model B the ratios of equations (7) at the nesting stage $n = 2$ within the two broad groups produce the following two estimating equations:

$$\ln\left(\frac{w_{HIGH\ SCHOOL,t}}{w_{NO\ DEGREE,t}}\right) = time - \frac{1}{\sigma_{EDU,L}} \ln\left(\frac{L_{HIGH\ SCHOOL,t}}{L_{NO\ DEGREE,t}}\right) + u_{L,t} \tag{14}$$

$$\ln(\frac{w_{COLLEGE,t}}{w_{SOME\ COLLEGE,t}}) = time - \frac{1}{\sigma_{EDU,H}} \ln\left(\frac{L_{COLLEGE,t}}{L_{SOME,COLLEGE,t}}\right) + u_{H,t} \tag{15}$$

They both assume that relative productivities follow a time trend plus a random term uncorrelated with relative supplies. Column 2 and 3 of Table 5 report the estimates of $-1/\sigma_{EDU,L}$ and $-1/\sigma_{EDU,H}$ respectively.[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 $-1/\sigma_{EDU,L}$ 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 $-1/\sigma_{EDU,L} = -0.32$ (a value that corresponds to the lowest estimate of $-1/\sigma_{H-L}$) is 258, thus rejecting the null hypothesis of $-1/\sigma_{EDU,L} = -1/\sigma_{H-L}$ at an overwhelming level of confidence. The estimate of $-1/\sigma_{EDU,H}$ is around -0.10. Again, the hypotheses $-1/\sigma_{EDU,H} = -0.32$ and $-1/\sigma_{EDU,H} = -1/\sigma_{H-L}$ are rejected.

Hence, three important results emerge from Table 5. First, the restriction $-1/\sigma_{EDU,H} = -1/\sigma_{EDU,L} = -1/\sigma_{H-L}$ is overwhelmingly rejected by the data. This provides evidence that model B better fits the time-series CPS data than model A. Second, the estimates of $-1/\sigma_{H-L}$ are between -0.32 and -0.66 averaging at -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) ranging between 1.5 and 2.5. Third, the estimated value of $-1/\sigma_{EDU,L}$ is between -0.039 and 0, implying an elasticity of substitution between workers with high school degree and those with no high school of 25 or above.

30 The corresponding estimates using wages calculated on the male sample only are available in the Table A.5 of the on-line appendix.

The reason for the extremely different estimates of $-1/\sigma_{EDU,L}$ and $-1/\sigma_{H-L}$ is readily spotted observing the de-trended 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 (de-trended) wages and supplies, a clear sign of negative correlation resulting in negative and significant $-1/\sigma_{EDU,H}$. To the contrary, Figure 8 shows no movement at all of relative wages vis-a-vis the very large fluctuations of the relative de-trended relative supplies similar in direction and larger in magnitude than those of Figure 7. This results in $-1/\sigma_{EDU,L}$ close to 0.

To sum up, CPS data suggest that reasonable estimates are in the neighborhood of -0.5 for $-1/\sigma_{EDU,H}$ and between -0.10 and 0 for $-1/\sigma_{EDU,L}$ and $-1/\sigma_{EDU,H}$ with the first coefficient closer to 0.10 and the second closer to 0. Accordingly, while one needs a good amount of caution 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 $\sigma_{EDU,H}$ and $\sigma_{EDU,L}$ both larger than or equal to10.

5 Wage Effects of U.S. Immigration

In the 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} (around 5) between any pair of experience groups, and for an elasticity of substitution σ_N around 20 between natives and immigrants with 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 12.5 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 $\sigma_{EDU,H}$ and $\sigma_{EDU,L}$ larger than or equal to 10 between their narrow education groups. On the other hand, if one still wanted to use models A and D as a robustness check, it would be reasonable to adopt the median estimate of σ_{EDU} equal to 2.5.

Whereas 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 U.S. in the period 1990-2006 by comparing the implications of models A, B and D based on the corresponding estimated elasticities.

5.1 The Fallacy of Partial Effects

Most existing empirical studies on the effect of immigration on wages (including Borjas, Freeman and Katz, 1997; Card, 2001; Friedberg, 2001; Section IV – but not Section VII – of Borjas, 2003; and Borjas, 2006) carefully estimate what Section 2.5 has called the *direct partial wage effect* of immigration within the same skill group and treat it as "the effect of immigration on wages".[31] As illustrated in that section, this partial wage effect (11) does not give complete information about the overall effect of immigration on wages. Indeed, to evaluate the *total wage effect*, we need to consider the entire distribution of immigrants across skill groups and all the cross effects among such groups.

The partial elasticity (11) is likely to be negative as long as immigrants are closer substitutes for natives in the same education-experience group than they are to natives in other skill groups. For instance, in models A and B expression (11) implies that the direct partial wage effect of immigrants in education-experience group k is[32]:

$$\frac{\Delta w_{D,k}}{w_{D,k}} \approx -\left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_N}\right)\frac{\Delta L_{F,k}}{L_{F,k} + L_{D,k}}$$

Using the estimates of $1/\sigma_N$ around 0.05 and $1/\sigma_{EXP}$ around 0.20 from Tables 2 and 3, the term $-\left(1/\sigma_{EXP} - 1/\sigma_N\right)$ is calculated around -0.15. Accordingly, for constant labor supply in all other groups, an inflow of immigrants increasing labor supply in group k 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 by 11.4% in total hours worked in the U.S. due to immigration caused a decrease by $-1.7\% = (-0.15 * 11.4\%)$ 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 a generalization would be misleading as expression (11) 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 5.2, 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% do not bear any resemblance to the total wage effects simulated below.

[31] The recent meta-study by Longhi, Nijkamp and Poot (2005) considers this partial effect as the relevant estimate across studies.

[32] The formula below uses expression 11 plus the fact that the share of immigrant employment in a skill group is similar to their share in the wage bill of the group.

5.2 Total Wage Effects

We are now ready to calculate the total effects of immigration on the wages of U.S.- and foreign-born workers. Specifically, we use the estimated elasticities in Tables 2 to 5 and the data on actual immigrant flows by skill group in Column 3 of Table 1 (together with the appropriate wage shares) to calculate the percentage impacts of immigration in any skill group on the wages of each skill group as implied by expressions (9) and (10). We then aggregate all these impacts to obtain averages for specific sets of workers.[33].

Table 6 reports the simulations of the total wage effects of immigration over the 1990-2006 period, for both U.S.- and foreign-born workers in the long run. We focus on 1990-2006 as this was the period of fastest immigration growth in recent U.S. history.[34] As highlighted in the top row of the table, we consider only 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 few rows of the table. The wage change in each education group for foreign- and U.S.-born workers is obtained by weighting the percentage total wage change of each experience-education group by its wage share in the education group.[35] This provides the entries in the rows labeled "less than HS" , "HS graduates", "Some CO" and "CO graduates". We also average the changes across education groups for US- and foreign-born workers separately, again weighting them 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 reported in the last row labeled "Overall Average".[36]

Turning to columns, Column 1 shows the simulated wage effects using model A and the parameter combination estimated on Census data, except for σ_N that is taken to be infinity. Such combination of parameters is essentially the one adopted by Borjas (2003) and Borjas and Katz (2007). Column 2 and 3 present simulations using the same nesting model and parameter combination as Column 1, except for σ_N whose value here is the one estimated in Table 1. We either impose that this is equal for all groups using the average estimate $\sigma_N = 20$ (Column 2) or we allow it to differ across education groups using $\sigma_N = 12.5$ for high school degree or less and $\sigma_N = 33$ for some college education or more (Column 3). These are the average estimates from Table 2. In Columns 4 and 5 we use the same parameter configuration as in Columns 2 and 3 but within model D. Finally, Columns 6 to 9 show the results obtained using 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. The other parameter values are unchanged, except for Column 9 where we test the effect of

[33] The detailed formulas relative to model B are described in Appendix A.2. The formulas for the other models are analogous. The STATA codes to implement the formulas for all models are available in the on-line appendix.

[34] Net immigration decreased in 2007 and 2008 and it was negative in 2009.

[35] Weighting by wage shares is dictated by the nested-CES structure.

[36] The table reports the "long run" effects, after capital has fully adjusted to the labor supply shock caused by the inflow of foreign-born workers. Recall that in our theoretical framework the overall average wage effect is always zero in the long run. See Section 2.

modifying σ_{EXP}.[37]

Let us first compare the results reported in Column 1 with perfect substitutability between native and immigrants, with those in Columns 2 or 3 with imperfect substitutability between them. Three main differences emerge. First, the wage loss of the least educated native workers is reduced by -1 to -1.8 percentage points. Given that in Column 1 it is estimated at -4.1 percentage points, that loss is reduced by a quarter to a half of its absolute value. Second, on average all the other native groups gain a bit more more (or lose a bit less less) in Columns 2 and 3 relative to Column 1. In fact, natives as a whole gain 0.6% of their average wage in Column 3. Third, the gains of natives in Column 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: on average, natives gain 0.6 to 0.7% of their wages whereas previous immigrants lose 6.6 to 7% of their wages.

The results for model D in Columns 4 and 5 are very similar to those of model A. Hence, 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 to 9 report the wage effects in model B, which Section 4.2.2 has shown to be preferred by the data. In light of that section, these columns set $\sigma_{H-L} = 2$ and $\sigma_{EDU,H} = \sigma_{EDU,L} = 10$, assuming imperfect substitutability between natives and immigrants either equal across groups (Column 6) or education-specific (Columns 7 to 9). In particular, Column 8 uses $\sigma_{H-L} = 1.41$, which is the exact KM estimate, and in Column 9 we test how sensitive results are to changing σ_{EXP} to 10. The wage effects are quite similar across all columns. Interestingly, the losses of less educated natives are either extremely small (-0.1%) or are even turned into gains (0.6%). Natives still gain as a group (0.6% of their average wages) and immigrant 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 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 $\sigma_{EDU,L}$ plays a fundamental role in determining the relative wage effects, and a value as low as 2.5 (Column 1) produces much larger effects relative to the preferred value of 10 used in Columns 6 to 9. Indeed, in these specifications the negative effect on least educated natives from the tilted distribution of immigrants towards lower educational levels is balanced or more than balanced by the positive effects from their imperfect substitutability. That is why even the least educated natives have either no or a small positive effect from immigration. The wage loss of less educated previous

[37] Columns 6 to 9 are indeed rather conservative as we use $\sigma_{EDU,L} = 10$, whereas the estimates in Section 4.2.2 suggest higher, and possibly infinite, values.

immigrants is between 8 and 10%. 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.[38]

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 effects of immigration as these estimate only the effect of direct competition and the total wage effect is also determined by indirect complementarities of 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 12.5). 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 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 (above 10) is strongly supported by the data. Also consistent with the labor literature, we found the elasticity of substitution between workers with some college education or more and those with 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 of immigration and a very small negative impact on wages of less educated natives. Other variations in nesting or elasticity assumptions (such as 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

[38] The corresponding results are not reported but are available on request.

allowed for, over the period 1990-2006 immigration to the U.S. had at most a modest negative long-run effect on the real wages of the least educated natives. This effect is between -3.1% and -0.1% depending on the chosen nesting structure, with the result closest to zero 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. In this respect, we hope that our modeling strategy, as well as our estimates and simulations, can provide a unified reference point for current and future debate on the wage effects of immigration in the U.S..

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A Theory Appendix

A.1 Income Shares in the Nested-CES

Given (2), the labor demand for workers in category d is

$$L_d = \frac{(w_d/\theta_d)^{-\sigma_D}}{\sum_d (w_d/\theta_d)^{1-\sigma_D}} \sum_d w_d L_d \tag{16}$$

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

$$s_d \equiv \frac{w_d L_d}{\sum_d w_d L_d} = \theta_d \frac{(w_d/\theta_d)^{1-\sigma_D}}{\sum_d (w_d/\theta_d)^{1-\sigma_D}} \tag{17}$$

On the other hand, differentiation of (2) yields

$$\frac{dL}{dL_d} = \theta_d \left(\frac{L}{L_d}\right)^{\frac{1}{\sigma_D}} \tag{18}$$

Then, (16), (17) and (18) 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 (7) 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

$$\begin{aligned}\left(\frac{\Delta w^D_{i(N-1)}}{w^D_{i(N-1)}}\right)^{Total} = & \frac{1}{\sigma_{H-L}} \sum_{H-L}\sum_{EDU}\sum_{EXP} \left(s^0_{j(N-1),F}\frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right) \\ & + \left(\frac{1}{\sigma_{EDU,i}} - \frac{1}{\sigma_{H-L}}\right)\sum_{EDU}\sum_{EXP}\left(s^1_{j(N-1),F}\frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right) \\ & + \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{EDU,i}}\right)\sum_{EXP}\left(s^2_{j(N-1),F}\frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right) \\ & + \left(\frac{1}{\sigma_N} - \frac{1}{\sigma_{EXP}}\right)\left(s^3_{j(N-1),F}\frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)\end{aligned} \tag{19}$$

and

$$\left(\frac{\Delta w^F_{i(N-1)}}{w^F_{i(N-1)}}\right)^{Total} = \frac{1}{\sigma_{H-L}}\sum_{H-L}\sum_{EDU}\sum_{EXP}\left(s^0_{j(N-1),F}\frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right) \tag{20}$$
$$+\left(\frac{1}{\sigma_{EDU,i}}-\frac{1}{\sigma_{H-L}}\right)\sum_{EDU}\sum_{EXP}\left(s^1_{j(N-1),F}\frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)+$$
$$+\left(\frac{1}{\sigma_{EXP}}-\frac{1}{\sigma_{EDU,i}}\right)\sum_{EXP}\left(s^2_{j(N-1),F}\frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)$$
$$+\left(\frac{1}{\sigma_N}-\frac{1}{\sigma_{EXP}}\right)\left(s^3_{j(N-1),F}\frac{\Delta L_{F,j(N-1)}}{L_{F,j(N-1)}}\right)-\frac{1}{\sigma_N}\frac{\Delta L_{F,i(N-1)}}{L_{F,i(N-1)}}$$

where $w^D_{i(N-1)}$ is the wage of domestic workers in group $i(N-1)$, $s^m_{j(N-1),F}$ 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

$$\overline{w}_t = \sum_{H-L}\sum_{EDU}\sum_{EXP}(w^F_{i(N-1)}\varkappa_{i(N-1),F} + w^D_{i(N-1)}\varkappa_{i(N-1),D})$$

where $\varkappa_{i(N-1),F}$ ($\varkappa_{i(N-1),D}$) are the hours worked by immigrants (natives) of 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:

$$\overline{w}_{Ft} = \frac{\sum_{H-L}\sum_{EDU}\sum_{EXP}(w^F_{i(N-1)}\varkappa_{i(N-1),F})}{\sum_{H-L}\sum_{EDU}\sum_{EXP}\varkappa_{i(N-1),F}}$$

and

$$\overline{w}_{Dt} = \frac{\sum_{H-L}\sum_{EDU}\sum_{EXP}(w^D_{i(N-1)}\varkappa_{i(N-1),D})}{\sum_{H-L}\sum_{EDU}\sum_{EXP}\varkappa_{i(N-1),D}}$$

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:

$$\frac{\Delta\overline{w}_{Dt}}{\overline{w}_{Dt}} = \frac{\sum_{H-L}\sum_{EDU}\sum_{EXP}\left(\frac{\Delta w^D_{i(N-1)}}{w^D_{i(N-1)}}\frac{w^D_{i(N-1)}}{\overline{w}_{Dt}}\varkappa_{i(N-1),D}\right)}{\sum_{H-L}\sum_{EDU}\sum_{EXP}\varkappa_{i(N-1),D}} = \frac{\sum_{H-L}\sum_{EDU}\sum_{EXP}\left(\frac{\Delta w^D_{i(N-1)}}{w^D_{i(N-1)}}\right)s^0_{j(N-1),D}}{\sum_{H-L}\sum_{EDU}\sum_{EXP}s^0_{j(N-1),D}} \tag{21}$$

where $\Delta w^D_{i(N-1)}/w^D_{i(N-1)}$ represents the percentage change in the wage of U.S.-born in group $i(N-1)$ due to immigration, and its expression is given in (19). Similarly, the percentage change in the average wage of foreign-born workers is:

$$\frac{\Delta\overline{w}_{Ft}}{\overline{w}_{Ft}} = \frac{\sum\limits_{H-L}\sum\limits_{EDU}\sum\limits_{EXP}\left(\frac{\Delta w^F_{i(N-1)}}{w^F_{i(N-1)}}\frac{w^F_{i(N-1)}}{\overline{w}_{Ft}}\varkappa_{i(N-1),F}\right)}{\sum\limits_{H-L}\sum\limits_{EDU}\sum\limits_{EXP}\varkappa_{i(N-1),F}} = \frac{\sum\limits_{H-L}\sum\limits_{EDU}\sum\limits_{EXP}\left(\frac{\Delta w^F_{i(N-1)}}{w^F_{i(N-1)}}\right)s^0_{j(N-1),F}}{\sum\limits_{H-L}\sum\limits_{EDU}\sum\limits_{EXP}s^0_{j(N-1),F}} \tag{22}$$

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 (20). 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:

$$\frac{\Delta\overline{w}_t}{\overline{w}_t} = \sum_{H-L}\sum_{EDU}\sum_{EXP}\left(\frac{\Delta w^F_{i(N-1)}}{w^F_{i(N-1)}}s^0_{j(N-1),F} + \frac{\Delta w^D_{i(N-1)}}{w^D_{i(N-1)}}s^0_{j(N-1),D}\right) \tag{23}$$

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.

B Data Appendix

B.1 IPUMS Census Data

We downloaded the IPUMS data on June 1st, 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 U.S.- 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 U.S.- 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 April 28th, 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 U.S.- 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 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), page 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 on-line appendix to the present paper.

Tables

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%**

Table 2

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

National Census and ACS, U.S. data 1960-2006

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**		
			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)	(0.15)	(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)
			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)
			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: Each cell reports the estimate of the parameter $-1/\sigma_N$. from specification (12) in the text. Method of estimation is Least Squares. In parenthesis we report the heteroskedasticity-robust standard errors, clustered over the 32 education-experience groups. In specification 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.

Table 3
Estimates of $(-1/\sigma_{EXP})$
(National Census and ACS U.S. data 1960-2006)

Structure of the nest	**Model A and B**	**Model C**		**Model D**
	(1)	**(2)**	**(3)**	**(4)**
Estimated coefficient:	$(-1/\sigma_{EXP})$	$(-1/\sigma_{EXP})$	$(-1/\sigma_{Y\text{-}O})$	$(-1/\sigma_{EXP})$
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: Each cell reports the estimates from a different regression that implements equation (7) 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 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.

Table 4
Estimates of ($-1/\sigma_{EDU}$)
(National Census and ACS, U.S. data 1960-2006)

	Model A		Model D	
Specification:	**(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: Each cell reports the estimates from a different regression that implements (7) 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 column 3 and 4.
*, **, *** = significant at the 10, 5 and 1% level.

Table 5

Elasticity of substitution between Broad and Narrow Education groups
CPS data 1962-2006, Pooled Men and Women

	Model B			
	(1) **$-1/\sigma_{H-L}$**	**(2)** **$-1/\sigma_{EDU,L}$**	**(3)** **$-1/\sigma_{EDU,H}$**	**Observations**
"Some College" split between L_{HIGH} and L_{LOW}	-0.54*** (0.06) [0.07]	-0.029 (0.018) [0.021]	-0.16* (0.08) [0.10]	44
"Some College" in L_{HIGH}	-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: Each cell is the estimate from a separate regression on 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.

Table 6
Calculated Long-Run Wage Effects of Immigration, 1990-2006

Nesting Structures:	Model A/C			Model D		Model B			
Specifications:	**(1)** $\sigma_N=\infty$	**(2)** Estimated σ_N	**(3)** Education specific σ_N	**(4)** Estimated σ_N	**(5)** Education specific σ_N	**(6)** Estimated σ_N	**(7)** Education specific σ_N	**(8)** Katz-Murphy $\sigma_{HIGH\text{-}LOW}$	**(9)** $\sigma_{EXP}=10$
Parameters:									
$\sigma_{HIGH\text{-}LOW}$	**2.5**	**2.5**	**2.5**	**2.5**	**2.5**	**2**	**2**	**1.41**	**2**
$\sigma_{EDU,HIGH}$	**2.5**	**2.5**	**2.5**	**2.5**	**2.5**	**10**	**10**	**10**	**10**
$\sigma_{EDU,LOW}$	**2.5**	**2.5**	**2.5**	**2.5**	**2.5**	**10**	**10**	**10**	**10**
σ_{EXP}	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**10**
$(\sigma_N)_H$	**∞**	**20**	**33**	**20**	**33**	**20**	**33**	**33**	**33**
$(\sigma_N)_L$	**∞**	**20**	**12.5**	**20**	**12.5**	**20**	**12.5**	**12.5**	**12.5**
% Real Wage Change of US-Born Workers Due to Immigration, 1990-2006									
Less than HS	-4.1%	-3.1%	-2.3%	-2.6%	-1.9%	-0.1%	0.6%	0.5%	0.6%
HS graduates	0.9%	1.4%	1.6%	1.4%	1.7%	0.5%	0.8%	0.7%	0.8%
Some CO	2.2%	2.5%	2.4%	2.4%	2.3%	1.0%	0.8%	0.9%	0.8%
CO graduates	-1.4%	-0.6%	-1.0%	-0.7%	-1.0%	0.5%	0.2%	0.2%	0.2%
Average US-born	**0.0%**	**0.7%**	**0.6%**	**0.7%**	**0.6%**	**0.6%**	**0.6%**	**0.6%**	**0.6%**
% Real Wage Change of Foreign-Born Workers Due to Immigration, 1990-2006									
Less than HS	-4.1%	-8.4%	-11.0%	-8.5%	-11.0%	-5.5%	-8.0%	-8.1%	-8.0%
HS graduates	0.9%	-6.1%	-10.2%	-6.0%	-10.1%	-6.9%	-11.0%	-11.1%	-11.0%
Some CO	2.2%	-2.4%	-0.6%	-2.5%	-1.0%	-4.0%	-2.2%	-2.1%	-2.2%
CO graduates	-1.4%	-9.2%	-6.3%	-9.3%	-6.7%	-8.1%	-5.0%	-5.0%	-5.0%
Average Foreign-born	**0.0%**	**-7.0%**	**-6.6%**	**-7.0%**	**-6.9%**	**-6.5%**	**-6.1%**	**-6.1%**	**-6.1%**
Overall average	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**

Note: The percentage wage changes for each education group are obtained averaging the wage change of each education-experience group (calculated using the formulas for the appropriate nesting structure and the coefficient listed in the first 6 rows). Those percentage changes are weighted by the wage share in the education group. The US-born and Foreign-born average changes are obtained weighting changes 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.

Figures

Figure 1: Alternative nesting models

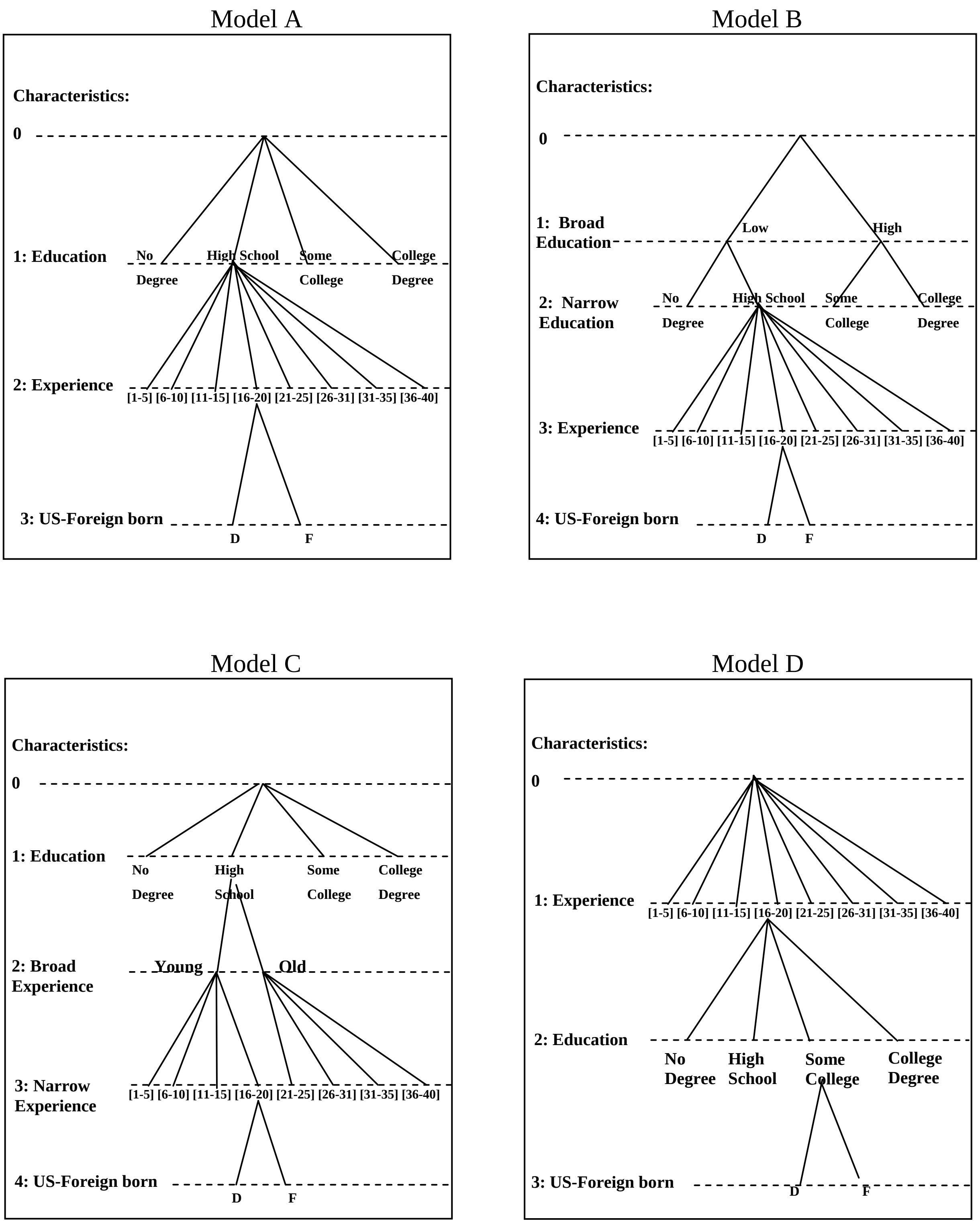
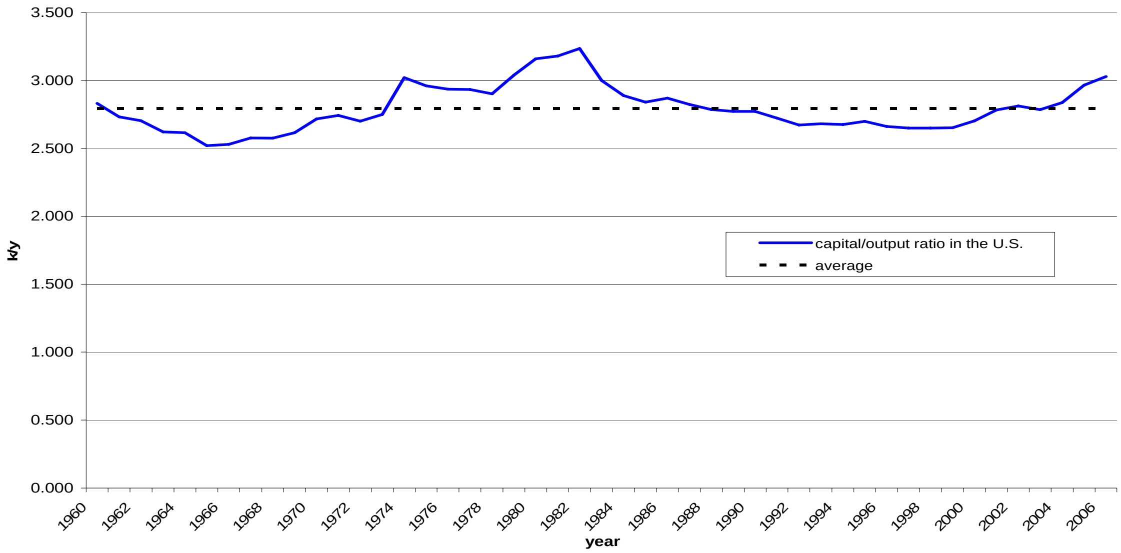
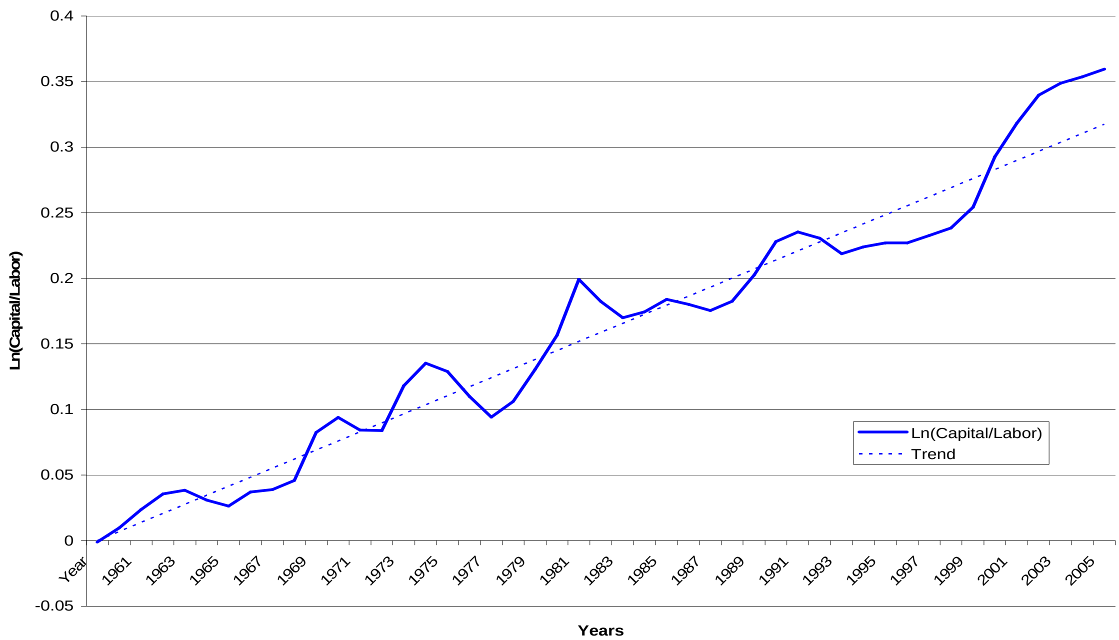


Figure 2
U.S. Capital-Output Ratio 1960-2006



Source: Authors' calculations using BEA data on the Stock of Physical Capital and GDP

Figure 3
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 non-farm employment.

Figure 4
Scheme of the CES Nests and Relative Notation

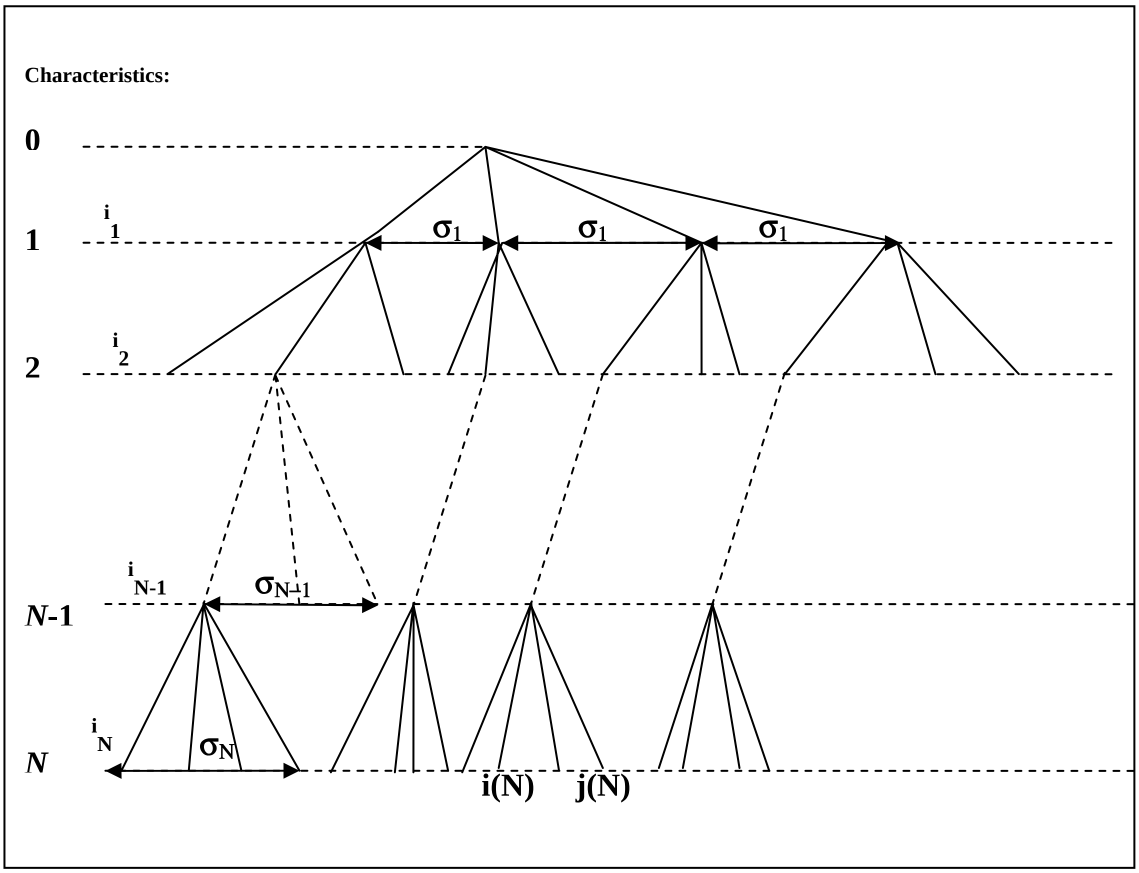
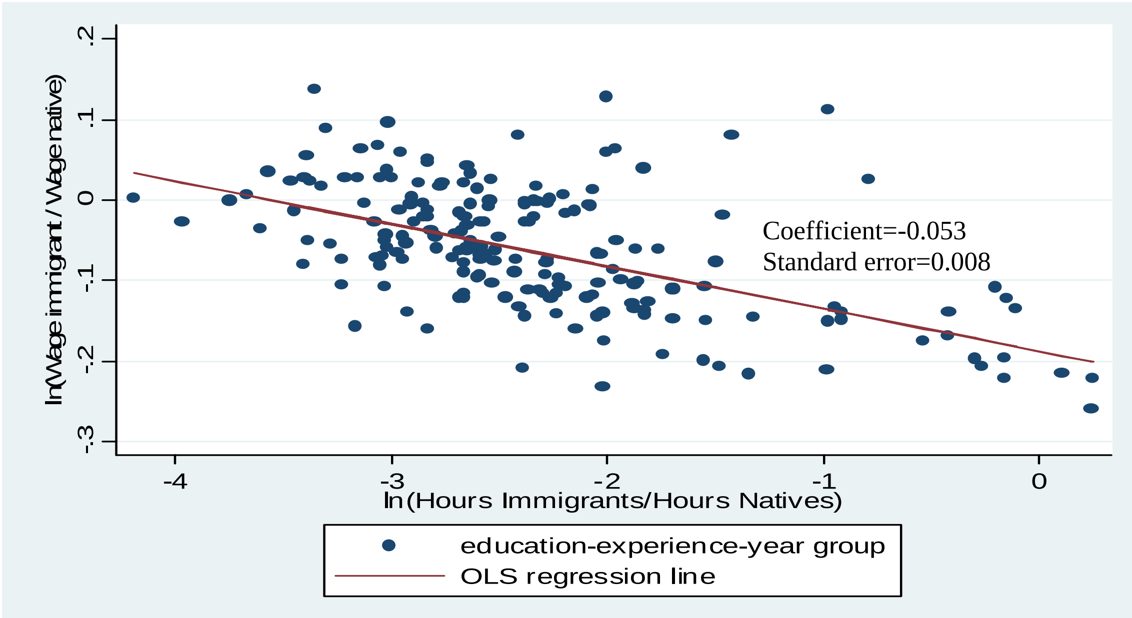
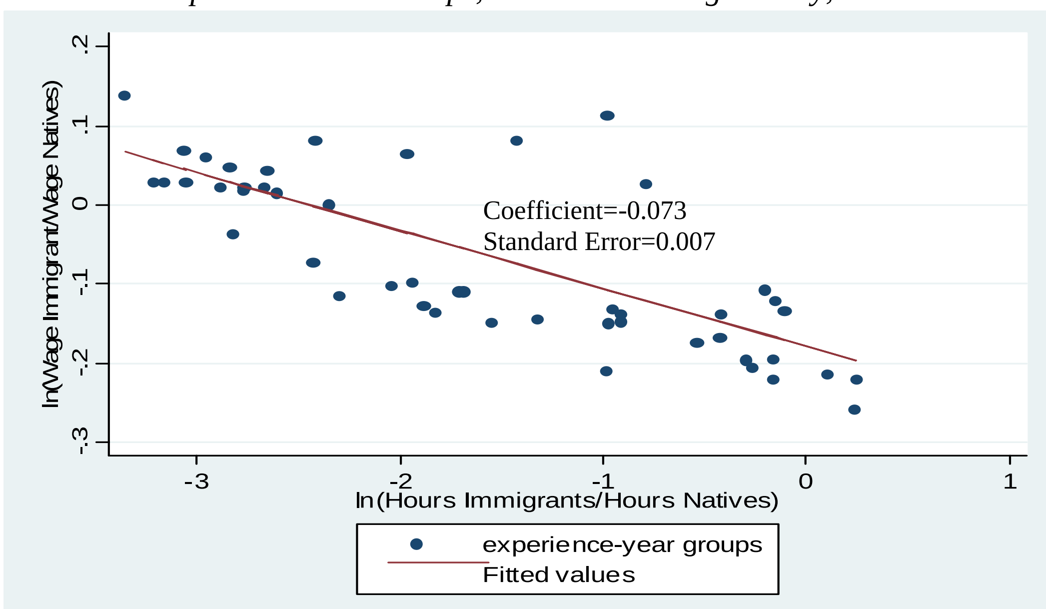


Figure 5
Correlation between relative wages and hours worked, Immigrant-Natives.
Cells are Education-Experience-Year Groups. Men, 1960-2006.



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.

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 an experience group in one of the years (1960, 1970, 1980, 1990, 2000, and 2006) for the group of workers with no schooling degree. Same variables as in figure 5

Figure 7
Relative Supply and relative wages:
(College and More)/(High School or Less) 1963-2006

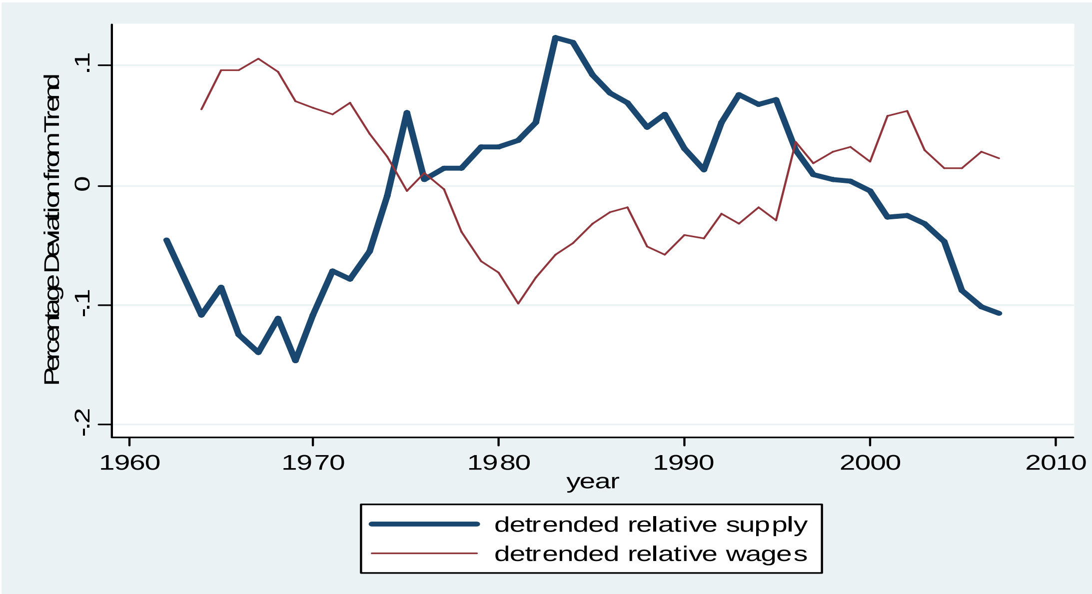


Figure 8
Relative Supply and relative wages:
(High School Graduates)/(No degree) 1963-2006