Immigration and National Wages:

Clarifying the Theory and the Empirics

Gianmarco I.P. Ottaviano, (Universita' di Bologna and CEPR)

Giovanni Peri, (University of California, Davis and NBER)*

July 2008

Abstract

This paper estimates the effects of immigration on wages of native workers at the national U.S. level. Following Borjas (2003) we focus on national labor markets for workers of different skills and we enrich his methodology and refine previous estimates. We emphasize that a production function framework is needed to combine workers of different skills in order to evaluate the competition as well as cross-skill complementary effects of immigrants on wages. We also emphasize the importance (and estimate the value) of the elasticity of substitution between workers with at most a high school degree and those without one. Since the two groups turn out to be close substitutes, this strongly dilutes the effects of competition between immigrants and workers with no degree. We then estimate the substitutability between natives and immigrants and we find a small but significant degree of imperfect substitution which further decreases the competitive effect of immigrants. Finally, we account for the short run and long run adjustment of capital in response to immigration. Using our estimates and Census data we find that immigration (1990-2006) had *small negative* effects in the *short run* on native workers with no high school degree (-0.7%) and on average wages (-0.4%) while it had *small positive effects* on native workers with no high school degree (+0.3%) and on average native wages (+0.6%) in the *long run*. These results are perfectly in line with the estimated aggregate elasticities in the labor literature since Katz and Murphy (1992). We also find a wage effect of new immigrants on previous immigrants in the order of negative 6%.

Key Words: Skill Complementarities, Less Educated Workers, Wages, Physical Capital Adjustment.

JEL Codes: F22, J61, J31.

*Gianmarco I.P. Ottaviano, Department of Economics, University of Bologna, Piazza Scaravilli 2, 40126 Bologna, Italy. Email: gianmarco.ottaviano@unibo.it. Giovanni Peri, Department of Economics, UC Davis, One Shields Avenue, Davis, CA 95616. Email: gperi@ucdavis.edu. Some sections of this paper incorporate methods and procedures contained in the previous NBER Working Paper # 12496, "Rethinking the Effect of Immigration on Wages". All estimates are, however, updated and new. We thank David Card, Steve Raphael, and Chad Sparber for very helpful discussions and comments. Greg Wright provided excellent research assistance. Ottaviano gratefully acknowledges funding from the European Commission and MIUR. Peri gratefully acknowledges funding from the John D. and Catherine T. MacArthur Foundation.

1 Introduction

There is a long tradition of finding small and often insignificant effects of immigration on the wages of native workers when analyzing cross-city and cross-state evidence in the US.[1] Two recent influential contributions, however, (Borjas, 2003; Borjas and Katz, 2007) have emphasized the importance of estimating immigration effects using national level U.S. data. In practice, this approach has found a significant negative effect of immigration on the wages of less educated natives, producing what has been considered a vindication of the relative labor supply theory which predicts that the large inflow of less educated immigrants into the U.S. since 1980 should have reduced the relative wages of less educated natives. This paper reconsiders and extends the national approach applied in Borjas (2003) and Borjas and Katz (2007) and demonstrates that the negative effects previously calculated are, to a large extent, the results of parameter restrictions not adopted in the rest of the labor and macro literature and not supported by empirical evidence. In particular, the finding of a large negative impact on wages of less educated immigrants is largely driven by an imprecise and, in our view, erroneous estimate of the elasticity of substitution between workers with a high school degree and workers with no degree. Moreover, in Borjas (2003) the failure to account for capital adjustment in the short run adds an implausibly large negative effect to native wages in the short run.

Our paper extends this so-called "national approach." First, we produce and use a more plausible estimate of the elasticity of substitution between workers with a high school degree and workers without one. Our estimates of that elasticity are quite large, rather precise and in line with the practice of the rest of the labor literature. Second, we identify a small but significant degree of imperfect substitutability between native and immigrant workers within the same education-experience group. This estimate revises and qualifies the previous estimates produced in Borjas, Grogger and Hanson (2008). We show that while very demanding specifications such as the one used by Borjas, Grogger and Hanson (2008) may produce insignificant values for the inverse elasticity because of large standard errors, in most reasonable estimates (based on sample selection criteria identical to theirs) the estimates of inverse elasticity are significant and around 0.05. Finally, and in our view most importantly, this article emphasizes the need for a general equilibrium approach based on a production function that accounts for direct and cross-skill effects of supply (immigration) on wages, as well as for capital adjustment. It is impossible using national data and six census years only to estimate the within-group and across-group effects freely, that is without imposing some restrictions. In a model with a rich set of skills such as the 32 education and experience groups used in Borjas (2003) and Borjas and Katz (2007) there would be 992 of those cross effects and using Census data only 192 skill by year observations are available since 1960. Hence, studies that do not explicitly describe the underlying structure of interactions are only able to estimate the *partial* effect of immigration within a group (for given supply in other groups) and not the actual effect

[1] See the influential review by Friedberg and Hunt (1995) and since then Card (2001), Card and Lewis (2007) and Card (2007).

of immigration on wages of native workers in each skill group. We show in section 6.1 how misleading it is to apply the partial elasticity estimate when evaluating the aggregate effect of immigration. Indeed, "[t]he labor demand curve is downward sloping", as Borjas (2003) puts it, but one should not forget that the demand for each factor (type of workers) shifts when the supplies of other factors change.

The model that we propose adopts a widely used nested CES production function which allows us to combine supply shocks affecting workers of different education and experience levels in order to identify wage effects. Two features of the production structure are important and widely accepted in the labor, macro and growth literatures. First, workers are grouped into two labor aggregates, highly educated (H) and less educated (L), and those are then combined into a labor aggregate (N) via a constant elasticity of substitution between the two groups, σ_{HL}. Typically workers with at least some college education are included in the group of highly educated and those with a high school education and less are in the other. Second, the labor aggregate (N) and the capital stock (K) are combined in a Cobb-Douglas production function since there is abundant evidence for the U.S. that the elasticity of substitution between them is one and that in the medium-to-long run capital adjusts to increases in labor so as to maintain constant rates of return (in the balanced growth path) and a constant capital-output ratio.

One could further differentiate workers by their education levels within the groups H and L. The literature, however, generally assumes an infinite elasticity of substitution between workers with no degree and those with a high school degree (we will call this elasticity σ_{LL}) and also perfect substitutability between those with some college education and college graduates (we will call their elasticity of substitution σ_{HH}). Given the fundamental importance of these two parameters in determining the effects of immigrants on the wages of less and more educated workers, and given scant existing estimates of them, we devote some effort to developing reasonable estimates of their values. More common is to separate workers according to their experience level within education groups (Card and Lemieux 2001, Welch 1979), allowing for imperfect substitutability across them (with an elasticity of substitution across experience groups σ_{EXP}). A CES combination of experience groups (nested within the education groups) can then be used to estimate the elasticities across groups. As estimates of the parameters $\sigma_{HL}, \sigma_{HH}, \sigma_{LL}$ and σ_{EXP} exist in the literature, one can adopt those estimates, place them in the CES production function, and use the inflow of immigrants in each group to calculate the effects on wages of natives of different education and experience levels. This is what we do in section 6.2, and then we also use our own estimates of the relevant parameters (produced in section 5) and show that they are remarkably similar to what is obtained using the parameters taken from the literature. Finally, the richness of our model allows us to differentiate more precisely the effect of immigration on wages of natives and previous immigrants.

Our estimation strategy has new features that significantly depart from Borjas (2003) and Borjas and Katz

(2007), and this has important consequences for the effects of immigration. First, using CPS data we estimate a specific elasticity between high school graduates and workers with no high school degree and show that it is rather high– in fact, much higher than the elasticity between college graduates and high school graduates. Second, we identify and estimate the elasticity between natives and immigrants within education-experience groups (σ_{IMMI}) and show that, while it is large, it is precisely estimated in many specifications (except the most demanding in terms of dummies). In most cases it is around 20. We also confirm the estimates found in the literature for the elasticity of substitution between workers of different experience groups within the same education group.

After combining the high substitutability between workers with no high school degree and high school graduates with the imperfect substitutability between natives and immigrants, the actual long run effect of immigration during the period 1990-2006 on wages of natives with no degree was very small, ranging between -0.5% and +0.7%. Even in the short run (i.e., as of 2007) accounting for the sluggish adjustment of capital, the negative impact of immigrants on wages of native workers with no degree was only -0.7%. The explanation for such a small effect on the group of less educated workers is intuitive. Immigration has been quite balanced between workers with a high school degree or less (L) and workers with some college education or more (H) but *within* the low education group (L) immigrants with no high school degree were a much larger share of the group than immigrants with a high school degree. Given the estimated high substitutability between those two types of workers (σ_{LL} is routinely assumed to be infinity in the labor literature) the effect of immigrants is diluted to the whole L group rather than concentrated among workers with no high school degree. This attenuates much of the competition effect that is due to immigrants. In the aggregate it is hard to discern any negative effect of immigrants on native wages for less educated and even allowing for perfect substitution between natives and immigrants we at most get a negative long-run effect of -0.6% on their wages as response to immigration 1990-2006.

At the same time, the estimated imperfect substitutability of natives and immigrants produces in the long run a small positive effect on wages of native workers with higher education (+0.5 to 1.0%), as well as on average native wages (+0.6%). A simulation which assumes perfect substitutability between natives and immigrants generates a wage loss for less educated U.S.-born workers of -0.6% or less over 16 years of immigration (1990-2006). Our preferred simulations, using a small degree of imperfect substitution between natives and immigrants, imply a small gain for the less educated natives (+0.3%), a positive effect for native workers with some college education or more (between +0.5 and 1%) and a positive average wage effect for natives overall of around +0.5% in the long run. We find a significant negative effect (on the order of -5 to -8% depending on their education) of new immigrants on the wages of previous immigrants. Two things reinforce our conviction of the validity of our results. First, our simulated wage effects on natives are perfectly consistent with previous estimates of the relative demand elasticities across education and experience groups in the labor literature. In fact, as we show in section 6, very similar wage effects for each education group could be obtained using our production function, immigration as a supply shock and elasticity estimates taken exclusively from the previous labor literature (e.g., Katz and Murphy, 1992; Welch, 1979; Card and Lemieux, 2001). Moreover, the simulated wage effects are also consistent with the cross-city effects of immigration estimated by most authors using the so-called "area approach" (e.g., Card, 2001; Card and Lewis, 2007).

The remainder of the paper is organized as follows. Section 2 frames this contribution within the existing literature on the national effects of immigration on wages and relates our model and estimates to the existing labor literature on the effects of different kinds of labor supply and labor demand shocks. Section 3 presents in detail the production function and the simple mechanism of adjustment of capital to labor supply. It derives the effects of immigration, considered as an increase in the supply of labor of different types, on wages (marginal productivity) of native and foreign-born workers of different types and on average. Section 4 describes the data, the criteria of sample selection and how we construct the main variables, and presents some summary statistics and trends. Section 5 describes the empirical strategy and discusses the estimates of the crucial elasticities (σ_{IMMI}, σ_{EXP}, σ_{HL}, σ_{LL} and σ_{HH}). Section 6 uses the estimated parameters to calculate the long run and the short run effect on wages of immigration over the period 1990-2006. We compare systematically our simulation results with those obtained using parameter estimates from the previous labor literature and with those obtained using the production function and estimates from Borjas (2003) and Borjas and Katz (2007). We also compare our simulated effects with those found using the cross-area analysis and reconcile the two approaches. Section 7 provides some final remarks.

2 Review of the Literature

This review is not exhaustive.[2] There is a long list of contributions in the literature dealing with the impact of immigrants on the wages of natives. Some of these studies explicitly consider the contribution of immigration to increased wage dispersion and to the poor performance of real wages of the least educated since 1980. Two questions are typically analyzed by the existing literature. The first is imbued with a "macro" flavor: Does the inflow of foreign-born workers have a positive or negative net effect on the average productivity and wages of U.S.-born workers? This question requires that we aggregate the wages of heterogeneous workers. The second question is more "micro" (or distributional) in focus: How are the gains and losses from immigration distributed across U.S.-born workers (and previous immigrants) with different levels of education? The consensus emerging from the literature is that the first (macro) effect on average U.S. wages is negligible in the long run, as capital

[2] For a recent and articulate overview of the estimates of the effect of immigration on wages see Longhi, Nijkamp and Poot (2005).

accumulates to restore the pre-migration capital-labor ratio. However, how long does it take to achieve the long run capital adjustment? As for the effects of immigration on the relative wages of more and less educated U.S.-born workers, some economists argue for a large, adverse impact on less educated workers (Borjas, 1994, 1999, 2003; Borjas, Freeman and Katz, 1997; Borjas and Katz, 2007), while others favor a smaller, possibly insignificant, effect (Butcher and Card, 1991; Card, 1990; Card, 2001; Friedberg, 2001; Lewis, 2005; National Research Council, 1997). The first group of economists argues that most of the negative effects are only identified if one looks at national data, and are missed by the cross-area approach.[3] They have therefore strongly advocated analysis based on national labor markets.

This paper, in fact, is most closely related to three previous papers that focus exclusively on the national market, specify a production function structure which combines workers of different skills, estimate parameters using national data, and then use these parameters to simulate the impact of immigration on wages. Those papers are Borjas (2003), Borjas and Katz (2007) and Ottaviano and Peri (2006a). The novel contributions of this paper relative to Borjas (2003) and Borjas and Katz (2007) are to consider carefully the mechanism of capital adjustment, to estimate the elasticity between workers with a high school diploma and those without a diploma, and to analyze the implications of imperfect substitutability between natives and immigrants. The novelty relative to Ottaviano and Peri (2006a) is the more careful structure of nesting education groups, the new estimates of the elasticity between workers with a high school diploma and those without a diploma (σ_{LL}) and the more careful, theory-based approach to the estimate of imperfect substitution between natives and immigrant workers (σ_{IMMI}). Let us add that in the last few years other studies have followed the lead of Ottaviano and Peri (2006a) and estimated the parameter $1/\ \sigma_{IMMI}$ within similar models for different samples and countries. Raphael (2008), using US data 1970-2005, Manacorda et al. (2005) using UK data, and D'Amuri et al. (2008) using German data. These articles all find small, but significant values for $1/\ \sigma_{IMMI}$ using specifications similar to the one we use in this paper (with fewer dummies than in Ottaviano and Peri, 2006a). Moreover, in the previous 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, page 468-469 for a discussion of this issue). Until Ottaviano and Peri (2006a), however, only a very few studies explicitly estimated the elasticity of substitution between natives and immigrants. Jaeger (1996) only covered metropolitan areas over 1980-1990, obtaining estimates that may be susceptible to attenuation bias and endogeneity problems related to the use of local data, and Cortes (2006), who considers low-skilled workers and uses metropolitan area data, finds a rather low elasticity of substitution between U.S.- and foreign-born workers.

Two other branches of the labor literature also provide much needed background for this paper. The first

[3]We will refer more systematically to other studies that estimate the effect of immigrants on US wages across cities and states in section 6.4, where we reconcile our results with those of the so-called "area approach."

branch is the one estimating the substitutability of workers with different education levels and simulating the impact of labor demand and supply shocks on wages. Beginning with Katz and Murphy (1992) and continuing with Murphy and Welch (1992), Angrist (1995), Autor, Katz and Krueger (1998), Johnson (1997), Krusell et al. (2000) and Acemoglu (2002), economists have argued that in order to understand the impact of changes in the supply and demand for labor on the wages of workers of different education levels it is very helpful to consider highly educated and less educated workers as imperfectly substitutable (with constant elasticity). Those studies classified workers with some college education or more as highly educated and all others as less educated. Appealing to its simplicity, this two-group structure has also been advocated on the basis of the observation that the wages of workers within the same group (e.g., workers with no degree or with a high school degree) seem to co-move much more than do the wages of workers in different groups (such as high school graduates and college graduates).[4] Borjas(2003), Borjas and Katz (2007) and Ottaviano and Peri (2006a), however, opt for four symmetric education groups combined in the CES (no degree, a high school diploma, some college and a college degree). Logically, such a structure is harder to believe as it assumes symmetry among four groups that have a natural ordering in their proximity, and it gives rise to very imprecise and often non-significant estimates of the elasticity $1/\ \sigma_{HL}$ (see Borjas, 2003, page 1364 and Borjas and Katz, 2007, footnote 28). Moreover, this four-group CES is not adopted by other articles that we know of in the labor literature. Hence we submit it to closer scrutiny, allowing for four education groups but testing their elasticity of substitution in a nested structure that can accommodate both the standard specification (of two large groups and perfect substitution within them) and the Borjas (2003) specification (with four groups), which we then test against each other.

The other branch of the labor literature providing useful reference analyzes the effect of age structure on the experience premium. Katz and Murphy (1992) consider a simple two group, young-old structure and find an elasticity of substitution between them of around 3.3. Welch (1979) and Card and Lemieux (2001) use a symmetric CES structure with several age groups and estimate elasticities between 5 and 10. While one could also revisit the symmetric CES structure along the experience dimension, the issue of immigration and its impact is much more focussed on the impact on the less educated (rather than of a particular age group). Since the relevance of the parameter σ_{EXP} is much smaller in determining the impact across education groups we are satisfied with reproducing the literature estimates in this case.

Finally, with respect to the treatment of physical capital, we explicitly consider its contribution to production and treat its accumulation as driven by market forces which equalize its real returns in the long run. In particular, we revise the usual approach that considers capital as fixed in short run simulations (Borjas, 2003; Borjas and Katz, 2007). The growth literature (Islam, 1995; Caselli, et al. 1996) and real business cycle literature (e.g., Romer, 2006, Chapter 4) have estimated, using annual data on capital accumulation and different types of

[4]See, for instance, Katz and Murphy (1992), page 68.

shocks, the speed of adjustment of capital to deviations from its long run growth path. Adopting 10% per year as a reasonable estimate of the speed of adjustment of physical capital in the U.S. (confirmed by our own estimates for the 1960-2006 period) we analyze the impact of yearly immigration on average wages as capital adjusts. We can evaluate the impact of immigration which occurred in the period 1990-2006 on average wages as of 2007, and we can evaluate its effects after five or ten more years.

3 Theoretical Framework

This paper treats immigration as a labor supply shock, omitting any productivity impact that it may produce (due to improved efficiency, choice of better technologies or scale externalities) and therefore may miss part of its positive impact on wages (identified often as a positive overall wage effect in cross-city or cross-state analyses such as Card, 2007, or Ottaviano and Peri 2005, 2006b). In order to evaluate the effects of immigrants on the wages of natives and other foreign-born workers with similar or different education and experience we need a model of how the marginal productivity of a given type of worker changes in response to changes in the supply of other types. We also need to account for capital adjustment. This essentially amounts to assuming a production function that parametrizes the elasticity of substitution between each type of worker and a simple model of capital adjustment in the short and long run. Our goal is to rely on a model which is acceptable to most economists. In particular, the structure of the labor market, the grouping of workers within skill cells, the functional form that is assumed in aggregating different skills and the elasticities of substitution used in the model should be consistent with best practices in the recent labor literature. Similarly, the treatment of substitutability between capital and labor and the adjustment of capital in the short and long run should be compatible with best practices in the recent macro and growth literature.

3.1 Production Function

The aggregate production function we use is the very common and popular Cobb-Douglas aggregation, broadly used in the macro and growth literature:

$$Y_t = A_t N_t^{\alpha} K_t^{1-\alpha} \tag{1}$$

where Y_t is aggregate output , A_t is exogenous total factor productivity (TFP), K_t is physical capital, N_t is a CES aggregate of different types of labor (described below), and $\alpha \in (0, 1)$ is the income share of labor. All variables, as indicated by the subscripts, are relative to year t. The production function is a constant returns to scale (CRS) Cobb-Douglas combination of capital K_t and labor N_t. This functional form has been widely used in the macro-growth literature (from Solow, 1956, to recent papers by Jones, 2005 and Caselli and Coleman,

2006) and is supported by the empirical observation that the share of income going to labor, α, is reasonably constant in the long run as well as across countries (Kaldor, 1961; Gollin, 2002)[5]. The labor aggregate N_t is defined as[6]:

$$N_t = \left[\theta_{Ht} N_{Ht}^{\frac{\sigma_{HL}-1}{\sigma_{HL}}} + \theta_{Lt} N_{Lt}^{\frac{\sigma_{HL}-1}{\sigma_{HL}}}\right]^{\frac{\sigma_{HL}}{\sigma_{HL}-1}} \quad (2)$$

where N_{Ht} and N_{Lt} are respectively aggregate measures of the labor supplied by workers with high (H) and low (L) education levels in year t, and θ_{Ht} and θ_{Lt} are productivity levels specific to workers with high and low education (standardized so that $\theta_{Ht} + \theta_{Lt} = 1$ and any common multiplying factor can be absorbed in the TFP term A_t). Finally, the parameter σ_{HL} is the elasticity of substitution between the two groups.

While the above specification is clearly a simplification, it is one that is broadly accepted and popular in the literature and presents several advantages. Above all, the fact that estimates of the parameter σ_{HL} exist in the literature allows us to potentially rely on those values to evaluate the effects of immigration on wages of workers with different educational attainments. The consensus value for σ_{HL} is usually identified as 1.5.[7] An important question is which level of education to include in each of the two groups. Most of the previous studies either include among highly educated workers those with a college degree or more (Autor, Katz and Krueger, 1998; Krusell et al., 2000), and leave all the other workers in the L group or they include workers with a high school degree or less in the group L, place college graduates in the group H, and split workers with some college nearly equally between the two groups (Katz and Murphy 1992; Card and Lemieux 2001; Welch 1979). At odds with both traditions, however, is the literature which uses the national approach to analyze the impact of immigration (Borjas 2003; Borjas and Katz 2007; Ottaviano and Peri 2006a). These papers choose a CES aggregator of 4 education groups (Some High School, High School Graduates, Some College, College Graduates) with a common and identical elasticity of substitution across all groups equal to σ_{EDU}. Restricting the elasticity across the four education groups to be the same may be required in order to obtain an estimate of σ_{EDU} when using Census data (due to the very few observations over time) but it is clearly suspicious. First, the education groups are not "symmetric" since workers with no degree are clearly more similar to those with a high school degree than to those with a college degree. Second, the existing estimates of σ_{EDU} in Borjas (2003) and Borjas and Katz (2007) are so imprecise that they are consistent with any value of σ_{EDU} from 1.5 to infinity (more on this in section 5.3). Hence, rather than assuming either the specification with four symmetric groups or the more established two education group approach, we nest the four education group specification

[5] 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 phisical capital complements highly educated and substitutes for less educated workers. Such an assumption, however, would imply, countrfactually, that the income share of capital increased over time following the large increase in supply and income share of highly educated. This has not happened in the U.S. over the period considered.

[6] This follows 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.

[7] See section 5.3 for a detailed review of the estimates of σ_{HL} in the literature.

used in Borjas (2003) into the more traditional two groups and use a production function which can encompass the two cases. Hence we assume that each labor composite N_{Ht} and N_{Lt} is itself the CES aggregate of two education subgroups:

$$N_{Lt} = \left[\theta_{SHSt} N_{SHSt}^{\frac{\sigma_{LL}-1}{\sigma_{LL}}} + \theta_{HSGt} N_{HSGt}^{\frac{\sigma_{LL}-1}{\sigma_{LL}}} \right]^{\frac{\sigma_{LL}}{\sigma_{LL}-1}} \tag{3}$$

$$N_{Ht} = \left[\theta_{SCOt} N_{SCOt}^{\frac{\sigma_{HH}-1}{\sigma_{HH}}} + \theta_{COGt} N_{COGt}^{\frac{\sigma_{HH}-1}{\sigma_{HH}}} \right]^{\frac{\sigma_{H}}{\sigma_{HH}-1}} \tag{4}$$

The terms N_{kt} for $k \in \{SHS, HSG, SCO, COG\}$ are aggregate measures of labor supplied by workers with, respectively, some high school education (SHS), a high school diploma (HSG), some college education (SCO) and a college degree (COG). The parameters θ_{kt} capture the relative productivity of those groups of workers within the aggregates N_{Lt} and N_{Ht}. The elasticities of substitution σ_{LL} and σ_{HH} capture, respectively, the degree of substitutability between workers with no high school degree and with a high school degree in expression (3) and the substitutability between workers with some college education and those with a college degree in expression (4). The nested structure above allows for, as specific cases, the more common two-group CES (for $\sigma_{LL}= \sigma_{HH} = \infty$ and $0 < \sigma_{HL} < \infty$) or the four-group Borjas (2003) CES (obtained for $\sigma_{LL}= \sigma_{HH} = \sigma_{HL} = \sigma_{EDU}$).[8] The estimate of the parameter σ_{LL}, as we will see, is extremely relevant in determining the effect of immigration on the wages of workers with no high school degree. However, there are no specific estimates of it in the literature and the common practice is to assume it is equal to ∞ and to aggregate workers with a high school degree or less together (usually weighted by different units of effective labor). We need, however, to collect more evidence on this parameter before accepting the assumption $\sigma_{LL} = \infty$ (used in most of the literature) rather than $\sigma_{LL}= \sigma_{HH} = \sigma_{HL}$ (preferred in Borjas 2003) and our structure allows us to do so using CPS data and the method used by Katz and Murphy (1992) (see section 5.3).

We then assume that within each N_{kt} are workers with different experience levels, who are also imperfect substitutes. In particular, following the specification used in Welch (1979) and Card and Lemieux (2001), we write:

$$N_{kt} = \left[\sum_{j=1}^{8} \theta_{kj} N_{kjt}^{\frac{\sigma_{EXP}-1}{\sigma_{EXP}}} \right]^{\frac{\sigma_{EXP}}{\sigma_{EXP}-1}} \tag{5}$$

where j is an index spanning experience intervals of five years between 0 and 40, so that $j = 1$ captures workers with $1 - 5$ years of experience, $j = 2$ those with $6 - 10$ years, and so on. The parameter $\sigma_{EXP} > 1$ measures the elasticity of substitution between workers in the same education group but with different experience levels and θ_{kj} are experience-education specific productivity levels (standardized so that $\sum_j \theta_{kj} = 1$ for each k and

[8] The nested case assumes a split between H and L that includes all workers with some college among highly educated. This is slightly different from the tradition of dividing them between the two groups and we will check empirically that it does not make a large difference in the estimate of σ_{HL}. A split of workers with some college between the two groups would further reduce the effect of immigration on wages.

assumed invariant over time, as in Borjas, 2003, Borjas and Katz , 2007, and Ottaviano and Peri, 2006a). The parameter σ_{EXP} is the elasticity of substitution between workers with the same education level and different experience. Finally, specific to the immigration literature and first introduced by Ottaviano and Peri (2006a), we define N_{kjt} as a CES aggregate of U.S.-born (domestic, D) and foreign-born (F) workers. Denoting the supply of labor by workers with education k and experience j who are, respectively, U.S.-born (Domestic) or foreign-born, by D_{kjt} and F_{kjt}, and the elasticity of substitution between them by $\sigma_{IMMI} > 0$, our assumption is that:

$$N_{kjt} = \left[\theta_{Dkj} D_{kjt}^{\frac{\sigma_{IMMI}-1}{\sigma_{IMMI}}} + \theta_{Fkj} F_{kjt}^{\frac{\sigma_{IMMI}-1}{\sigma_{IMMI}}} \right]^{\frac{\sigma_{IMMI}}{\sigma_{IMMI}-1}} \tag{6}$$

The terms θ_{Hkjt} and θ_{Fkjt} measure the specific productivity levels (relative quality) of foreign- and U.S.-born workers. They may vary across education-experience groups but (as with the θ_{kj} above) they are assumed to be invariant over time. They are standardized so that $(\theta_{Hkj} + \theta_{Fkj}) = 1$. Foreign-born workers are likely to have different abilities pertaining to language, quantitative skills, relational skills and so on. These characteristics, in turn, are likely to affect their choices regarding occupations and jobs, therefore foreign-born workers might be differentiated enough to be imperfect substitutes for U.S.-born workers, even within the same education and experience group.

3.2 Physical Capital Adjustment

Physical capital adjustment in response to immigration may not be immediate. However, investors respond continuously to inflows of labor and to the consequent increase in the marginal productivity of capital; how fast they respond is an empirical question. Further, immigration is not an unexpected and instantaneous shock. If we define the short run effect as the impact of immigration given a fixed capital stock, we can ask: for how long is capital fixed and why? Immigration is an ongoing phenomenon, distributed over years, predictable and rather slow. Despite the acceleration in legal and illegal immigration after 1990, the inflow of immigrants measured less than 0.6% of the labor force each year between 1960 and 2006. In a dynamic context the relevant parameter in order to evaluate the impact of immigration on average wages is the speed of adjustment of capital. In the long run, on the balanced growth path such as in the Ramsey (1928) or the Solow (1956) models, the variable $\ln(K_t/N_t)$ follows a constant positive trend growth determined only by the growth rate of total factor productivity ($\ln A_t$) and unaffected by the size of N_t. Therefore the average wage in the economy, which depends on K_t/N_t, does not depend on immigration in the long run. Shocks to N_t, such as immigration, however, may temporarily affect the value of K_t/N_t, causing it to be below its long run trend. How much and for how long $\ln(K_t/N_t)$ remains below trend as a consequence of immigration depends on the yearly inflow of immigrants and on the yearly rate of adjustment of physical capital. The theoretical and empirical literature on the speed of convergence of a country's capital per worker to its own balanced growth path (Islam, 1995; Caselli et al. 1996), as well as the business cycle literature on capital adjustment (see Romer, 2006, Chapter 4.7), provide estimates for this speed of adjustment that we can use together with data on yearly immigration to obtain the effect of immigration over 1990-2006 on average wages in 2007 and in the subsequent years as capital continues to adjust. We devote the next section, 3.2.1, to showing in detail the connection between average wages and the capital-labor ratio. In analyzing the simulated effects of immigrants we first focus on the long run effects (Section 6.2), allowing for full capital adjustment, as a natural reference. Then in Section 6.3 we use the estimated speed of capital adjustment (from the macro literature) to show the effect of sixteen years of immigration (1990-2006) on wages as of the year 2007, and we then compare those results with the traditional way of computing "short run" effects on wages.

3.2.1 Partial Adjustment, Total Adjustment and Wages

Given the production function in (1) the effect of physical capital K_t on the wages of individual workers operates through the effect on the marginal productivity of the aggregate N_t. Let us call w_t^N the compensation to the composite factor N_t, which is equal to the average wage in the economy[9]. In a competitive market it equals the marginal productivity of N_t, hence:

$$w_t^N = \frac{\partial Y_t}{\partial N_t} = \alpha A_t \left(\frac{K_t}{N_t}\right)^{1-\alpha} \tag{7}$$

Assuming either international capital mobility or capital accumulation along the balanced growth path of the Ramsey (1928) or Solow (1956) models, the real interest rate r and the aggregate capital-output ratio K_t/Y_t are both constant in the long run and the capital-labor ratio K_t/N_t grows at a constant rate equal to $\frac{1}{\alpha}$ times the growth rate of technology A_t. This assertion is also supported in the data, and is particularly true for our period of consideration, 1960-2006. As depicted in Figure 1 the capital-output ratio (K_t/Y_t) shows small deviations around a constant mean over the 46 years considered. And there is no evidence that in the period of fastest immigration (1990-2006) the ratio systematically deviated from its average. Moreover, the log capital-labor ratio, $\ln(K_t/N_t)$, shown in Figure 2 exhibits remarkably fast reversion to its long run trend (also shown in figure 2), as evidenced by the fact that the path of the variable crosses the trend eleven times in the sample. And again, there is no systematic evidence of a downward departure from the trend in the 1990-2006 period[10]. In order to show the effect of different patterns of capital adjustment on the average wage (w_t^N) it is useful to write the capital stock as $K_t = \kappa_t N_t$, where κ_t is the capital-labor ratio. Hence w_t^N (from equation

[9] The "average wage" w_t^N is obtained by averaging the wages of each group (by education, skill and nativity), weighting them by the share of the group in the total labor supply.

[10] We analyze the capital data and their dynamic behavior empirically in Section 6.3.

(7)) can be expressed in the following form:

$$w_t^N = \alpha A_t \left(\kappa_t\right)^{1-\alpha} \tag{8}$$

Calculating the marginal productivity of capital and equating it to the interest rate r, augmented by capital depreciation δ, we obtain the expression for the balanced growth path capital-labor ratio, $\kappa_t^* = \left(\frac{1-\alpha}{r+\delta}\right)^{\frac{1}{\alpha}} A_t^{\frac{1}{\alpha}}$. Substituting this into equation (8) implies that the average wage on the balanced growth path, $\left(w_t^L\right)^* = \alpha \left(\frac{1-\alpha}{r+\delta}\right)^{\frac{1-\alpha}{\alpha}} A_t^{\frac{1}{\alpha}}$, does not depend on the total supply of workers N_t. Hence, in the short run, the change in labor supply due to immigration affects average wages only if (and by the amount that) it affects the capital-labor ratio. Assuming that technological progress ($\Delta A_t/A_t$) is exogenous to the immigration process, the percentage change in average wages due to immigration can be expressed as a function of the percentage response of κ_t to immigration. Taking partial log changes of (8) relative to immigration we have:

$$\frac{\Delta w_t^N}{w_t^L} = (1-\alpha)\left(\frac{\Delta \kappa_t}{\kappa_t}\right)_{immigration} \tag{9}$$

where $(\Delta\kappa_t/\kappa_t)_{immigration}$ is the percentage deviation of the capital-labor ratio from κ_t^* due to immigration. With full capital adjustment and the economy on the balanced growth path, $(\Delta\kappa_t/\kappa_t)_{immigration}$ equals 0. At the same time, if one assumes fixed total capital, $K_t = \overline{K}$, then $(\Delta\kappa_t/\kappa_t)_{immigration}$ equals the negative percentage change of labor supply due to immigration: $-\frac{\Delta F_t}{N_t}$, where ΔF_t is the increase in labor supply due to foreign-born workers in the period considered and N_t is the aggregate labor supply at the beginning of the period. In the obviously counterfactual case in which we keep capital unchanged over sixteen years of immigration, 1990-2006, the inflow of immigrants increases the amount of hours worked by 11.4% of its total value in 1990. This, combined with a capital share $(1-\alpha)$ equal to 0.33, implies a negative effect on average wages of 3.8 percentage points. Accounting for the sluggish yearly response of capital and for yearly immigration flows, however, we can estimate the *actual* response of the capital-labor ratio to immigration flows in the 1990-2006 period, without the extreme assumption that capital be fixed for 16 years. We do this in Section 6.3 when we revisit the short and long run effects of immigration on wages.

3.3 Effects of Immigration on Wages

We use the production function (1) to calculate the demand functions and wages for each type of labor at a given point in time. Choosing output as the numeraire good, in a competitive equilibrium the (natural logarithm of) the marginal productivity of U.S.-born workers (D) equals (the natural logarithm of) their wage. Denoting the broad education level with $b \in B \equiv \{H, L\}$, the specific education level with $k \in E \equiv \{SHS, HSG, SCO, COG\}$ and the experience level with $j = 1, 2, ..., 8$, we can write the wage of a generic U.S.-born worker (equal to her marginal productivity) as:

$$\ln w_{Dbkjt} = \ln\left(\alpha A_t \kappa_t^{1-\alpha}\right) + \frac{1}{\sigma_{HL}}\ln(N_t) + \ln\theta_{bt} - \left(\frac{1}{\sigma_{HL}} - \frac{1}{\sigma_{bb}}\right)\ln(N_{bt}) + \ln\theta_{kt} - \left(\frac{1}{\sigma_{bb}} - \frac{1}{\sigma_{EXP}}\right)\ln(N_{kt}) + \ln\theta_{kj} - \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{IMMI}}\right)\ln(N_{kjt}) + \ln\theta_{Dkj} - \frac{1}{\sigma_{IMMI}}\ln(D_{kjt}) \tag{10}$$

Similarly, for a foreign-born worker in the same b, k, j skill group the wage is:

$$\ln w_{Fbkjt} = \ln\left(\alpha A_t \kappa_t^{1-\alpha}\right) + \frac{1}{\sigma_{HL}}\ln(N_t) + \ln\theta_{bt} - \left(\frac{1}{\sigma_{HL}} - \frac{1}{\sigma_{bb}}\right)\ln(N_{bt}) + \ln\theta_{kt} - \left(\frac{1}{\sigma_{bb}} - \frac{1}{\sigma_{EXP}}\right)\ln(N_{kt}) + \ln\theta_{kj} - \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{IMMI}}\right)\ln(N_{kjt}) + \ln\theta_{Fkj} - \frac{1}{\sigma_{IMMI}}\ln(F_{kjt}) \tag{11}$$

where D_{kjt} (F_{kjt}) represents the total labor input (hours worked) of male and female U.S.-born (foreign-born) workers of education k (in broad group b) and experience j and w_{Dbkjt} (w_{Fbkjt}) represents the average wage of the group. We assume that the relative efficiency parameters, represented by the θ's, as well as total factor productivity A_t, depend on technological factors and are independent of the supply of foreign-born.

Given (10) and (11), the overall impact of immigration on natives with education k and experience j can be decomposed into a positive effect that works through capital adjustment $\ln\left(\alpha A_t \kappa_t^{1-\alpha}\right)$ and four effects that operate through N_{kjt}, N_{kt}, $N_{bt}$and N_t. The corresponding expressions are reported in Appendix A. Here we provide the basic intuition. First, there is the positive overall effect of immigration on the productivity of workers in group b, k, j due to increased supply of all types of labor: a worker, whether native or immigrant, benefits from the increase in aggregate labor supply thanks to imperfectly substitutability among different types of workers. This effect operates through $\frac{1}{\sigma_{HL}}\ln(N_t)$. Second, there is the effect on marginal productivity generated by the supply of immigrants within the same broad education group (but different specific education group). This effect operates through the term $-\left(\frac{1}{\sigma_{HL}} - \frac{1}{\sigma_{bb}}\right)\ln(N_{bt})$. It is negative if workers with similar broad education are closer substitutes than workers with different broad education ($\sigma_{bb} > \sigma_{HL}$). Third, there is the effect due to the supply of immigrants within the same specific education group. This effect operates through $-\left(\frac{1}{\sigma_{bb}} - \frac{1}{\sigma_{EXP}}\right)\ln(N_{kt})$. It is negative if workers with similar education-experience are more substitutable than workers with the same education but different experience level ($\sigma_{EXP} > \sigma_{bb}$). Finally, while in (10) the stock of native workers D_{kjt} is unaffected by immigration, there is still an additional negative effect of immigrants on the wages of foreign born workers through $-\frac{1}{\sigma_{immi}}\ln(F_{kjt})$ in (11), which takes into account the fact that foreign-born workers may not be perfect substitutes for U.S.-born workers with equal skills and education.

Notice that the wages of native workers in group b, k, j are affected by a *direct partial* effect of immigrants in their same education-experience group plus 56 other *cross-effects* produced by immigrants in other groups and a capital-adjustment term. The *direct partial* effect, in fact, can be thought of as measuring the wage impact, keeping constant the aggregate supplies N_t, N_{bt} and N_{kt}. Such effects have been estimated, for instance, in sections II to VI of Borjas (2003) by regressing the wage of natives $\ln(w_{Hkjt})$ on the labor supply of immigrants in the same skill group b, k, j in a panel across groups and over census years, controlling for year-specific effects (absorbing the variation of N_t) and education-by-year specific effects (absorbing the variation of N_{bt} and N_{kt}). The resulting partial elasticity, expressed as the percentage variation of native wages $(\Delta w_{Dbkjt}/w_{Dbkjt})$ in response to the percentage variation of foreign employment in the group $(\Delta F_{bkjt}/F_{bkjt})$, is given by the following expression:

$$\varepsilon_{kjt}^{partial} = \left.\frac{\Delta w_{Dbkjt}/w_{Dbkjt}}{\Delta F_{bkjt}/F_{bkjt}}\right|_{N_{kt},N_{bt},N_t \text{ constant}} = \left[\left(\frac{1}{\sigma_{IMMI}} - \frac{1}{\sigma_{EXP}}\right)\left(\frac{s_{Fbkjt}}{s_{bkjt}}\right)\right] \tag{12}$$

where s_{Fbkjt} is the share of overall wages paid in year t to foreign-born workers in education group b, subgroup k, with experience j. Analogously, s_{bkjt} is the share of the total wage bill in year t accounted for by all workers in education group b, subgroup k and with experience j. Hence, by construction, the elasticity $\varepsilon_{kjt}^{partial}$ captures only the effect of immigration on native wages operating through the term $-\left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{IMMI}}\right)\ln(N_{kjt})$ in (10). While this term is likely to be negative (if $\sigma_{IMMI} > \sigma_{EXP}$), its value is clearly uninformative about the effect of overall immigration on the wages of native workers within the skill group. In fact, the total effect depends not only on the changes in the capital stock but also on the increased relative labor supply of all education and experience cells as well as on all the cross elasticities (σ_{HL}, σ_{bb}, σ_{EXP}, σ_{IMMI}). "The labor demand curve is downward sloping" (Borjas, 2003) in each cell, but it shifts when the supplies of other imperfectly substitutable factors change.

4 Data, Variables and Sample Description

A detailed description of the data, the exact specification of the samples and a step-by-step account of how each variable has been constructed can be found in Appendix B[11]. The variable definitions, construction and sample selection coincide exactly with those in Borjas, Grogger and Hanson (2008). The data we use are from the integrated public use microdata samples (IPUMS) of the U.S. Decennial Census and from the American Community Survey (Ruggles et al., 2008). In particular, we use the general 1% sample for Census 1960, the 1% State Sample, Form 1, for Census 1970, the 5% State sample for the Censuses 1980 and 1990, the 5% Census Sample for year 2000 and the 1% sample of the American Community Survey (ACS) Sample for the year 2006. The large size of the samples ensures a high level of precision in estimating our variables in each year. Since

[11] The STATA codes used to perform selection of samples, construction-averaging of variables by cell and all the regressions and simulations contained in this paper are available with detailed explanations at the website: http://www.econ.ucdavis.edu/faculty/gperi/codesOP2008.htm
The authors encourage interested researchers to use them duefully acknowledging the source.

they are all weighted samples we use the variable "personal weight" to produce the average and aggregate statistics below. 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 including all the hours worked in each education-experience-nativity (and sometimes gender) cell. It contains people aged 18 and older in the census year[12] not living in group quarters, who worked at least one week in the previous year.

To construct the measure of hours worked in each cell and year these workers are grouped into four schooling groups, eight experience groups and two nativity (US- and foreign-born) groups.[13] Schooling groups are constructed using the variable EDUCREC which classifies levels of education consistently across censuses and ACS data. The four groups identified are: individuals with no high school degree, high school graduates, individuals with some college education and college graduates. We define years of experience as years of potential experience. They are calculated using the variable "AGE" and with 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. Then we select only workers with experience of at least one year and less than or equal to forty years.[14] 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. The status of "foreign-born" is given to those workers who are non-citizens or are naturalized citizens (using the variable "CITIZEN" since 1970 and "BPL" in 1960). The hours of labor supplied by each worker are calculated by multiplying hours worked in a week by weeks worked in a year (see Appendix B for the exact definition and computational procedure) and individual hours are multiplied by the individual weight (PERWT) and aggregated within each education-experience group. This measure of hours worked by cell is the basic measure of labor supply. We also calculate (and alternatively use) the employment (count of employed people) by cell (summing up the personal weights for all people).

To construct the average wage in each cell we use a more selective sample since we want to be sure that we are measuring the correct average "price of labor" in the cell. Hence, from the employment sample we eliminate workers who do not report wages (or report 0 wages) and those who are self-employed (since it is hard to separate labor and non-labor income). In a second and more restrictive wage sample (used to produce the estimates of Table 3) we also eliminate workers still enrolled in school. 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 in its topcodes as described in Appendix B, divided by weeks worked

[12]While sixteen years of age is the cut-off chosen by the Bureau of Labor Statistics for those people who are defined as "working age" we choose the cut-off at eighteen (corresponding to seventeen in the census year) to conform with Borjas, Grogger and Hanson (2008).

[13]We also consider, in the regression analysis, cells with only male, only female or pooled male and female individuals. The summary statistics and the aggregate trends in this section are provided for the pooled sample of males and females together.

[14]This selection eliminates a sizeable group of young and old individuals with experience of 0 years or less (due to a misclassification of their initial age of work) and 41 or more.

in a year) and averaging them for each cell using weights equal to the hours worked by the individual times her personal weight. This is our preferred method to calculate wages because it includes wages of all workers, including part-time workers who constitute a large group in some cells, but weights their contribution to the average wage by their labor supply (hours worked).

The procedure described above allows us to construct the variables D_{bkjt}, F_{bkjt}, (hours worked) and w_{Dbkjt}, w_{Fbkjt} (average weekly wages) for domestic and foreign-born workers of each education level (in group b and subgroup k), experience level (j) and year t (1960, 1970, 1980, 1990, 2000 and 2006). Those are the basic variables used in the empirical analysis when estimating the elasticity parameters (section 5) and when simulating the effects of immigration (section 6). These variables also allow us to construct s_{Nbkjt} and $\varkappa_{Nbkjt}$, the share of each group in the total wage bill and in total hours worked for each represented year t. When estimating the production-function parameters (σ_{HL}, σ_{HH}, $\sigma_{LL}, \sigma_{EXP}$ and σ_{IMMI}) we always use the entire panel of data, 1960-2006. When we simulate the effects of immigration on real wages, using those estimates, we focus on the most recent period, 1990-2006. Before proceeding with the econometric analysis, let us present some salient features of the immigration and wage data and some informative trends and summary statistics.

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 most recent available in the data and the one on which we focus our simulations. One can see in Table A1 in the Table Appendix the evolution of immigrant labor supply (expressed as a percentage of hours worked) in each education-experience group over all the years considered (from 1960 to 2006). Also, Table A2 in the Table Appendix shows the real value (in 2000 constant U.S. \$) of weekly wages for U.S.-born workers in each group between 1960 and 2006 and Table A3 reports the ratio of immigrant to native weekly wages for each skill group and year in the entire sample.

Even a cursory look at the values in Column 3 of Table 1 reveals that the inflow of immigrants has been uneven across groups. Focussing on the rows marked “All Experience Groups”, in each of the four detailed 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 with some college education experienced only a 10% and 6% increase, respectively, in hours worked due to immigrants. Interestingly, however, such imbalances are drastically reduced if we consider the broad educational categories corresponding to highly educated (H) and less educated (L) in the model above. When we merge workers with a high school degree or less (see the row in the middle of Table 1) immigrant labor accounts for only 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 high school degree constitutes only a very small share of the total labor supply (only 8% of total hours worked in 2006 are supplied by workers with no degree versus 30% by workers with a high school degree). In comparison, the group of workers with some college education or a college degree experienced, during the same period, a 10% increase in hours worked because of immigrants (last row of Table 1). It is clear already from these numbers that the substitutability between the group of workers with no degree and those with a high school degree will be crucial in determining how much of the competition effect of immigrants on wages remains localized to the group of workers with no degree (for which immigrants constituted a relevant relative supply shock) and how much is diffused to the group of workers with at most a high school degree (for which immigration did not represent much of a relative supply shock).

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 negative correlation between increases in the share of immigrants and the real wage changes of natives across the detailed education groups. The group of workers with no high school degree received an increase in labor supply due to immigrants two to three times larger (in percentage terms) than the group of high school graduates or college dropouts, and the wage performance of the first group (-3.1%) is somewhat worse than the performance of the other two (-1.2% and -1.9%, respectively). However, the group of college graduates received the second largest increase in labor supply due to immigrants (+14.6%) and experienced by far the best wage performance (+9.6%). In fact, looking more closely at the performance of the group of workers with no degree, their negative wage performance seems to be exclusively due to the large, negative wage changes within the group of workers with more than 30 years of experience (who experienced a negative 9% change in their real wage). This group, however, received a relatively small inflow of immigrants (14.3 and 21.9%) compared to other experience groups with no high school degree some of which experienced more than 30% increase in size because of immigration. A look at Figures 3 and 4 conveys the same information in a more compact way. Figure 3 summarizes graphically the percentage increase in labor supply due to immigration in eight education-experience groups and Figure 4 shows the real wage change for the same groups, also during the 1990-2006 period. Rather than demonstrating a negative correlation of immigration and wages across education groups, which would produce two histograms that are mirror images of one another (one U-shaped and the other hump-shaped), the two charts suggest a possible positive association between the variables for education groups above high school and no association at all for the two histograms as a whole.

Obviously these partial and raw correlations do not reveal much about the actual effect of immigration on wages. It is time to use our model to estimate the crucial elasticities across groups of workers and calculate how much of the real wage variation observed in the data can be explained by changes in labor supply due to immigrants. In terms of the education groups described in this section the natural questions arising are: (i) How much of the negative performance in the wage of native dropouts in the 1990-2006 period was due to immigration within that group? (ii) How much of the college-high school dropout wage gap widening was due to immigration? (iii) Was there any effect of immigration on overall average wages of U.S.-born workers? We will address these questions in Section 6 below.

5 Parameter Estimates

5.1 Estimates of σ_{IMMI}

We begin with the estimation of the elasticity of substitution between smaller groups in the CES and progressively we aggregate those up to estimate elasticity between the larger aggregates. At the lowest level, foreign-born and natives are combined within each education-experience group with an elasticity of substitution equal to σ_{IMMI}. This parameter, first estimated in Ottaviano and Peri (2006a) has attracted a lot of attention and recent studies have produced estimates of it for the U.K. (Manacorda et al., 2006), for Germany (D'Amuri et al., 2008; Felbermayr, Geis and Kohler, 2008) and Borjas, Grogger and Hanson (2008) have re-estimated it for the U.S. Further evidence of imperfect substitution between native and foreign-born workers comes from a long list of studies in the past that found larger negative effects (within skill groups) of immigration on wages of previous immigrants relative to wages of native workers,[15] while several anecdotal stories as well as rigorous empirical evidence (see Ottaviano and Peri 2006a and Peri and Sparber 2008) emphasize that immigrants choose different occupations and jobs from natives and have different skills (manual versus language) even within similar education and age groups.

While the original Ottaviano and Peri (2006a) estimate of $\frac{1}{\sigma_{IMMI}}$ was probably too large we think that there is enough indirect and direct evidence of imperfect substitution[16] to deserve a careful second look at the Borjas, Grogger and Hanson (2008) estimates. This is important because even small degrees of imperfect substitution (as we will see in section 6) imply non-trivial differences on the effect of immigrants on wages of natives and previous immigrants. Moreover Borjas, Grogger and Hanson (2008) and Ottaviano and Peri (2006a) find relatively large standard errors and impose very demanding controls (in the form of sets of dummies) in the estimates of $\frac{1}{\sigma_{IMMI}}$. Such a large set of dummies is not justified by the theoretical framework used, nor is it in line with the procedure used to estimate the *other elasticities* of the model.

We proceed as follows. Taking the difference between expression (10) and expression (11) we obtain equation (13) below that provides the basis for the estimation of $\frac{1}{\sigma_{IMMI}}$:

[15] See, for instance, Grossman (1982) page 599, and Card (2001), Table 7. Longhi et al. (2005) summarize the literature and, considering nine previous studies using U.S. data, conclude that "...immigrants have a significantly bigger depressing effect on wages of other immigrants than on natives' wages" (page 468-69).

[16] A recent paper by Raphael and Smolensky (2008) also estimates $\frac{1}{\sigma_{IMMI}}$ for the U.S. finding a significant value in most cases. Discussions with Steve Raphael allowed us to understand in greater detail why Borjas et al. (2008) do not estimate a significant inverse elasticity.

$$\ln(w_{Fbkjt}/w_{Dbkjt}) = \ln(\frac{\theta_{Fkj}}{\theta_{Dkj}}) - \frac{1}{\sigma_{IMMI}}\ln(F_{kbjt}/D_{kbjt}) \quad (13)$$

where w_{Fbkjt}/w_{Dbkjt} is the relative wage of immigrants and U.S.-born workers in education group k (within broad group b), experience group j and period t; F_{kbjt}/D_{kbjt} measures the relative hours worked by the two groups and $\frac{\theta_{Fkj}}{\theta_{Dkj}}$ is the relative foreign-native productivity. Notice that in line with what is described in the model, it is reasonable to assume that $\frac{\theta_{Fkj}}{\theta_{Dkj}}$ varies across education-experience group but that it is constant over time. There are two very good reasons for this. First, remember that while technology affects the relative productivity of education (and experience) groups in different ways over time, such differences are absorbed by the $\theta's$ in the higher levels of the production function nesting. In equation (13) as we use *ratios* of wages and hours worked within education-experience-period groups one can allow technology to be specific to each education-experience-year and those specific terms all cancel out leaving only the relative "productivity" of immigrants and natives $\ln(\frac{\theta_{Fkj}}{\theta_{Dkj}})$. Second, the restriction of constant $\ln(\frac{\theta_{Fkj}}{\theta_{Dkj}})$ is perfectly in line with (in fact it is less restrictive than) the assumption made at the higher level of CES nesting. For instance the experience-specific productivity terms θ_{kj} are assumed to be constant over time. This is the assumption made in section 5.2 below as well as in Borjas (2003) (see section VII.A of the paper) and in Borjas and Katz (2007) (see section 1.4 of the paper) to estimate the elasticity σ_{EXP}. In our interpretation the term $\frac{\theta_{Fkj}}{\theta_{Dkj}}$ captures mostly the relative labor effectiveness (quality) of foreign-born versus natives. While we have reasons to believe that it may be related to the education-experience of the group it is much less clear that this changes systematically over time in a way correlated to the change in the percentage of immigrants. Hence, our basic regression to estimate $\frac{1}{\sigma_{IMMI}}$ is:

$$\ln(w_{Fbkjt}/w_{Dbkjt}) = I_{kj} - \frac{1}{\sigma_{IMMI}}\ln(F_{kbjt}/D_{kbjt}) + u_{kbjt} \quad (14)$$

Where I_{kj} are 32 education by experience fixed effects and u_{kbjt} is a group-specific error term. In the basic specifications (denoted as "basic") reported in Column (2) of Tables 2 and 3 we treat the error u_{kbjt} as potentially correlated within education-experience groups (hence the clustering of the standard errors) but with no other systematic component. To capture potential systematic changes of the relative productivity of foreign workers over time in the specifications reported in in column (3) of Table 2 and 3 (with the title "Add Time Effects") we allow also for a time-specific effect (I_t). If the systematic change in quality is due mostly to new immigrants (who have low levels of experience) one can think that we should include a systematic experience by time component (I_{jt}) and we do this in specifications of column (4) of Tables 2 and 3 labelled "Add Time by Experience effects". Finally, if the change in quality of young, less experienced immigrants over time is also systematically related to their education groups one can also include education by time effects (I_{kt}). We include all the interactions in the specifications of column (5) in Table 2 and 3 labelled as "Add Time by Education Effects". This last specification is identical to those estimated in Borjas, Grogger and Hanson (2008) and in column (6) we report their exact estimates of $\frac{1}{\sigma_{IMMI}}$ for the corresponding specifications, where available.

The problem of specifications in columns (5) and (6) is that the extremely large number of dummies (104) absorbs a very large part of the identifying variation (based on 192 observations at most). This causes a 3-4 fold increase in the standard errors (relative to the basic specification), reducing our ability to identify precisely the parameter. More importantly, such extreme saturation using dummies, when the variables are already ratios (rather than levels) within a cell, is a much more demanding method than what is applied to estimate *any other elasticity in the model.* We illustrate in section 5.2 and 5.3 below that the same issue applies to the estimate of the other inverse elasticities of the model, $\frac{1}{\sigma_{EXP}}$ and $\frac{1}{\sigma_{EDU}}$: saturating the variation in the education-year and experience-year dimensions with dummies makes the estimates insignificantly different from 0.

Before commenting on the regression results, reported in Tables 2 and 3, it is very useful to take a look at the data to see that the relative immigrant-native wages show a very clear negative correlation with the relative immigrant-native hours worked across groups and decades, the clear sign of imperfect substitution. Figure 5 simply shows the scatterplot of $\ln(w_{Fbkjt}/w_{Dbkjt})$ and $\ln(F_{kbjt}/D_{kbjt})$ defined above and the very significantly negative regression line (the coefficient is equal to 0.05, and the robust standard error, clustered by group, is equal to 0.007). Figure 6 shows the scatterplot once we subtract from each skill group the estimated fixed effect I_{kj}. The changes over time (relative to a group-specific average) of the relative immigrant-native hours supplied and weekly wages appear even more significantly negatively correlated with each other (the coefficient is equal to -0.06 and the robust standard error, clustered by group, is 0.008). The negative and significant correlation, very apparent from the data is "prima facie" evidence of imperfect substitution. The elasticity implied by such coefficients is around 20 and significantly different from ∞. Finally, even a very simple look at the data in Tables A1 and A3 confirms that groups experiencing large increases in the share of foreign-born (e.g. all workers with no degree and experience between 10 and 30 years) also underwent a significant deterioration in the wage of foreign-born relative to nationals.

Table 2 reports the estimated values of $\frac{1}{\sigma_{IMMI}}$ using our basic wage and employment sample (described in section 4) and specifications that include an increasing set of control dummies. As described above, beginning with specification (1) which does not include any dummy, we add education by experience effects (exactly as specified in expression 14) in specification (2). In specification (3) we add time effects, in (4) we also include time by experience effects and in (5) we add time by education effects. The first row includes only men, the second only women and the third men and women pooled in the calculation of the relative wages. As men and women may have different productive characteristics and differ in their attachment to the labor market it is traditional in this literature to prefer samples of men only. Our regressions show similar results when using either gender or a pooled sample. In the fourth row the method of estimation is 2SLS and the relative foreign-native employment in the group is used as instrument for relative hours worked, to reduce the potential endogeneity of hours worked to wage compensation. In the fifth row we restrict the sample to 1970-2006, as the share of foreign-born in employment only started increasing in the seventies. The sixth row shows the estimates obtained using only groups with high school education or less, the seventh row restrict the sample to the groups of workers with 20 years of experience or less.

Three robust results emerge from Table 2. First, all the full-sample specifications in columns (1) to (4) produce highly significant estimates of $-\frac{1}{\sigma_{IMMI}}$ ranging between -0.024 and -0.095 and mostly around -0.05, implying an elasticity $\sigma_{IMMI} = 20$. Second, the standard errors (robust and clustered by education-experience group) of those specifications in columns (1)-(4), including the whole sample (rows one to five), are generally below 0.015 and in the basic specifications (column 2) they are smaller or equal to 0.012. In contrast, the specifications that include all dummies (column 5) produce errors mostly larger then 0.03, and usually *three to four times larger* than for the basic specification. The estimates in Borjas, Grogger and Hanson (2008) are shown in column (6) next to our corresponding estimates (column 5). The only *very minor* differences between the two estimates (leading to very small numerical discrepancies) reside in our use of a simpler cell-size weighting (number of observations) in the regression (rather than the slightly more sophisticated weighting used in Borjas, Grogger and Hanson, 2008) and in the fact that we first take the average of cell wages to calculate w_{Fbkjt}/w_{Dbkjt} and then apply the logarithm (consistent with the theoretical model) to that ratio. Borjas, Grogger and Hanson (2008) take the average of logarithmic individual wages of native and immigrants in each cell, instead, and then subtract one from the other[17]. Comparing the Borjas, Grogger and Hanson (2008) estimates with the others in the same row it is clear that the large standard errors and insignificant estimates in their paper are a result of the saturation with dummies. While it is hard to determine which set of dummies capture important demand shocks, and to decide which set to include, we want to emphasize that the inclusion of similar sets of dummies (see sections 5.2 and 5.3 below) would make the estimates of *all inverse elasticities in this model statistically insignificant.*

Finally, in most specifications we find no appreciable difference in the estimates using men or women or both groups pooled. If anything the specification using men only, which is usually preferred in this literature, produces larger estimates of the inverse elasticity $\frac{1}{\sigma_{IMMI}}$ in the basic specification of column (2). Rows 4 and 5 of Table 2 (as well as Table A4 in the Appendix that separates all the results between men and women) present robustness checks. Using the 2SLS method (with relative employment instrumenting relative hours worked) and omitting observations for 1960 does not change significantly any result. In the last the two rows of Table 2, we inquire whether the small but significant degree of imperfect substitution, estimated using all groups is also

[17] We also run our regressions using their exact method and codes obtaining results essentially identical to those reported.

present restricting our sample to less educated or to young workers. Since the inflow of young, less educated immigrants is credited with the large competition effects on less educated natives it is relevant to check that even for those specific groups some degree of imperfect substitutability exists. While the estimates become somewhat more imprecise and in some instances a bit smaller, by and large they are still significant and usually around -0.05, even when we include all dummies. We take this as evidence that young and less educated native workers exhibit a significant, if small, degree of imperfect substitution with immigrants.

Table 3 does not need lengthy comment, as it reproduces Table 2 exactly except that in the sample in which we construct wages we eliminate (besides self-employed and workers reporting no wage) workers still attending school. We perform this check since Borjas, Grogger and Hanson (2008) argues that the estimates of $-\frac{1}{\sigma_{IMMI}}$ in Ottaviano and Peri (2006a) were significantly affected by the inclusion of individuals still attending school. While reproducing (essentially exactly) Borjas, Grogger and Hanson (2008) results in the "fully-dummy-saturated" regressions of column (5), Table 3 shows that the inclusion or exclusion of people attending school does not make any difference in the estimates of the basic specification and of all other specifications. We interpret the large imprecision of the estimates in column (5) and the stability of estimates in other columns as another sign that the relevant identifying variation in the data demonstrates imperfect substitutability which is in large part absorbed by the inclusion of the dummies. Notice that a formal test performed using even the coefficients and standard errors in column (5) of Table 2 or 3 only rejects once out of 14 times the hypothesis of $-\frac{1}{\sigma_{IMMI}} = -0.05$ at a 5% significance level. Hence, even the Borjas, Grogger and Hanson (2008) estimates cannot reject such a degree of imperfect substitution (i.e., an elasticity of 20). It is only that their standard errors are too large, and the identifying variation too small, to produce significant point estimates[18].

5.2 Estimates of σ_{EXP}

We can now use equation (14) to infer the systematic, time-invariant, components of the efficiency terms θ_{Dkj} and θ_{Fkj}. In particular, those terms can be obtained using the estimates of the fixed effects $\widehat{I}_{kj}$, from equation (14) and imposing the standardization that they add up to one for each education and experience group as follows:

$$\widehat{\theta}_{Fkj} = \frac{\exp(\widehat{I}_{kj})}{1+\exp(\widehat{I}_{kj})}, \widehat{\theta}_{Dkjt} = \frac{1}{1+\exp(\widehat{I}_{kj})} \tag{15}$$

Using the values of $\widehat{\theta}_{Dkj}$ and $\widehat{\theta}_{Fkjt}$ from above and the estimate $\widehat{\sigma}_{IMMI}$ we can construct the aggregate labor input, following (6), as $N_{kjt} = \left[\widehat{\theta}_{Dkj} D_{kjt}^{\frac{\widehat{\sigma}_{IMMI}-1}{\widehat{\sigma}_{IMMI}}} + \widehat{\theta}_{Fkj} F_{kjt}^{\frac{\widehat{\sigma}_{IMMI}-1}{\widehat{\sigma}_{IMMI}}}\right]^{\frac{\widehat{\sigma}_{IMMI}}{\widehat{\sigma}_{IMMI}-1}}$. Aggregating the marginal pricing conditions for each education-experience group (given by relations (10) and (11)) implies the following

[18] We also performed the regression specified in Table 2 using a wage sample that includes only full-year full-time workers. The estimates are almost identical to those presented in Table 2 and are available upon request..

relationship between the compensation going to the composite labor input N_{kjt} and its supply:

$$\begin{aligned}\ln(\overline{W}_{kjt}) &= \ln\left(\alpha A_t^{\frac{1}{\alpha}} \kappa_t^{\frac{1-\alpha}{\alpha}}\right) + \frac{1}{\sigma_{HL}}\ln(N_t) + \ln\theta_{bt} - \left(\frac{1}{\sigma_{HL}} - \frac{1}{\sigma_{bb}}\right)\ln(N_{bt}) + \ln\theta_{kt} \\ &- \left(\frac{1}{\sigma_{bb}} - \frac{1}{\sigma_{EXP}}\right)\ln(N_{kt}) + \ln\theta_{kj} - \frac{1}{\sigma_{EXP}}\ln(N_{kjt})\end{aligned} \tag{16}$$

where $\overline{W}_{kjt} = w_{Fbkjt}(F_{kjt}/N_{kjt}) + w_{Dbkjt}(D_{kjt}/N_{kjt})$ is the average wage paid to workers in the education-experience group k, j and can be considered as the compensation to one unit of the composite input N_{kjt}.[19] Equation (16) provides the basis for estimating the parameter $\frac{1}{\sigma_{EXP}}$, which measures the elasticity of relative demand for workers with identical education and different experience levels. Empirical implementation is achieved by rewriting it as:

$$\ln(\overline{W}_{kjt}) = I_t + I_{kt} + I_{kj} - \frac{1}{\sigma_{EXP}}\ln(\widehat{N}_{kjt}) + e_{kjt} \tag{17}$$

where the year fixed effects I_t control for the variation of $\ln\left(\alpha A_t^{\frac{1}{\alpha}} \kappa_t^{\frac{1-\alpha}{\alpha}}\right) + \frac{1}{\sigma_{HL}}\ln(N_t)$, the year by education fixed effects I_{kt} control for the variation of the term $\ln\theta_{bt} - \left(\frac{1}{\sigma_{HL}} - \frac{1}{\sigma_{bb}}\right)\ln(N_{bt}) + \ln\theta_{kt} - \left(\frac{1}{\sigma_{bb}} - \frac{1}{\sigma_{EXP}}\right)\ln(N_{kt})$ and education by experience fixed effects I_{kj} capture the terms $\ln\theta_{kj}$ that we assumed in section 3.1 constant over time. The term e_{kjt} represents a education-experience specific random disturbance. Notice that specification (17) requires the inclusion of the terms I_t and I_{kt} to absorb effects predicted by the model due to changes in the broader labor aggregates and their productivity. On the other hand, the term I_{kj} controls for education-experience specific productivity terms that are assumed constant over time. Such an identifying assumption follows closely Borjas (2003) (see section VII.A of the paper) and Borjas and Katz (2007) (see section 1.4 of the paper) and is exactly akin to the assumption made in the basic specification (14) above. Notice for instance that we (and the previous literature) do not include experience by time effects I_{jt} in estimating $\frac{1}{\sigma_{EXP}}$. As we see in Table 4 below, the saturation of the model with that extra set of dummies would reduce the estimates of $-\frac{1}{\sigma_{EXP}}$ to a value insignificantly different from 0.

Each cell of Table 4 reports the estimate of $-\frac{1}{\sigma_{EXP}}$ from a separate regression. In column (1) we implement regression (17) using the labor index $\ln(\widehat{N}_{kjt})$ constructed exactly as described above. We alternatively use a sample of men only (first row), women only (second row) or men and women pooled (third row). In the fourth row we use employment, rather than hours worked to construct $\ln(\widehat{N}_{kjt})$, and in the last row we omit year 1960. As the elasticity of substitution σ_{IMMI} is quite large, the construction of $\widehat{N}_{kjt}$ is not very dissimilar from simply adding hours worked by native and immigrants within the cell. Column (2) shows the results when we construct $\ln(\widehat{N}_{kjt})$ using the more intuitive sum of hours worked within the cell. The method of estimation in

[19] The wage $\overline{W}_{kjt}$ is an average of the wages paid to U.S.- and foreign-born workers in group k, j. The averaging weights are equal to the share of hours worked by each sub-group in the group k, j.

Table 4 is 2SLS using $\ln(F_{kjt})$, the hours worked by immigrants in the cell, as instrument for $\ln(\widehat{N}_{kjt})$. Once we control for the dummies immigration is considered as a pure supply shock and is used to instrument the variation of $\ln(\widehat{N}_{kjt})$. Column (3) departs from the basic specification by adding a set of time by experience fixed effects in the estimation. Its purpose is to illustrate the effect of absorbing with dummies a large part of the variation when estimating $-\frac{1}{\sigma_{EXP}}$. The reported standard errors are heteroskedasticity robust and clustered by education-experience group.

Before commenting on the results reported in Table 4 let us remind the reader that estimates of the elasticity $-\frac{1}{\sigma_{EXP}}$ exist in the literature. They use the variation in relative cohort size to estimate the effect on relative cohort wages. The most influential are the following three. First Welch, using five-year experience groups within four education groups (in a set-up similar to this paper) estimated a value of $-\frac{1}{\sigma_{EXP}}$ between -0.080 and -0.218 (see Table 7 and 8 of Welch, 1979) corresponding to an elasticity between 4.6 and 12. Then Katz and Murphy using only two experience groups (young, equivalent to 1-5 years of experience and old, equivalent to 26 to 35 years of experience) find $-\frac{1}{\sigma_{EXP}} = -0.342$ (footnote 23 in Katz and Murphy, 1992) equivalent to an elasticity of 3. Finally, in the most influential contribution Card and Lemieux (2001) using the supply variation due to the baby boomers' cohorts estimate a value of $-\frac{1}{\sigma_{EXP}}$ between -0.107 and -0.237 (Table V in Card and Lemieux, 2001) implying an elasticity between 4.2 and 9.3.

It is therefore reassuring to notice that the estimates of Column (1) and (2) of Table 4 relative to men and to the pooled sample are exactly in the range estimated by Welch (1979) as well as, for the large part, in the range estimated by Card and Lemieux (2001). The estimated $-\frac{1}{\sigma_{EXP}}$ ranges between -0.07 and -0.16. Only for the sample of women (second row) are the estimates imprecise and not significant – possibly due to larger heterogeneity of this sample because of the lower labor market attachment of women (most of the results of Welch, 1979, and Card and Lemieux, 2001, are based on men only). Notice also the extreme similarity of the results obtained by constructing $\ln(\widehat{N}_{kjt})$ in the more cumbersome model-based way (column 1) or simply adding hours worked in the cell (column 2). This is often the case when the sub-groups of workers exhibit high elasticity of substitution. All in all, our preferred estimated value of σ_{EXP} (using the men or pooled sample for the whole period) is between 6.2 and 7.7. and it is perfectly compatible with the estimates in Welch (1979) and Card and Lemieux (2001).

Finally, column (3) saturates the education-experience, experience-time and education-time variation with dummies and generates insignificant estimates of $-\frac{1}{\sigma_{EXP}}$. This is the same effect produced by dummy saturation in the estimates of $-\frac{1}{\sigma_{IMMI}}$ (in Column 5 of Tables 2 and 3) and shows the sensitivity of these elasticity estimates to the inclusion of an excessive number of dummies. In the light of the practice in the previous literature (including Borjas, 2003 and Borjas and Katz, 2007), of the existing estimates of $-\frac{1}{\sigma_{EXP}}$ and consistently with the previous section, we consider therefore specifications (1) and (2) as providing the relevant parameter estimates.

Essentially the estimates of σ_{EXP} in the literature range between 5 and 10 and our preferred estimates indicate a value between 6 and 8.

5.3 Estimates of σ_{HL}, σ_{LL} and σ_{HH}

5.3.1 Using the Model

Aggregating one level further, we can construct the CES composite $\widehat{N}_{kt}$. We obtain the estimates $\widehat{\theta}_{kj}$ from the experience by education fixed effects in regression (17), as follows: $\widehat{\theta}_{kj} = \exp(\widehat{I}_{kj})/\sum_j \exp(\widehat{I}_{kj})$. Then we use the estimated values of σ_{EXP} to construct, according to formula (5), $\widehat{N}_{kt} = \left[\sum_{j=1}^{8} \widehat{\theta}_{kj} N_{kjt}^{\frac{\widehat{\sigma}_{EXP}-1}{\widehat{\sigma}_{EXP}}}\right]^{\frac{\widehat{\sigma}_{EXP}}{\widehat{\sigma}_{EXP}-1}}$. The production function chosen, together with marginal cost pricing, implies that the compensation going to the labor input N_{kt} and its supply satisfy the following expression:

$$\ln(\overline{W}_{kt}) = \ln\left(\alpha A_t^{\frac{1}{\alpha}} \kappa_t^{\frac{1-\alpha}{\alpha}}\right) + \frac{1}{\sigma_{HL}}\ln(N_t) + \ln\theta_{bt} - \left(\frac{1}{\sigma_{HL}} - \frac{1}{\sigma_{bb}}\right)\ln(N_{bt}) + \ln\theta_{kt} - \frac{1}{\sigma_{bb}}\ln(N_{kt}) \tag{18}$$

where $\overline{W}_{kt} = \sum_j \left(\frac{N_{kjt}}{N_{kt}}\right)\overline{W}_{kjt}$ is the average wage in education group k[20] in broad group b. The problem of using the general formula (18) as basis for the empirical estimates of $\frac{1}{\sigma_{bb}}$ is that we only have 6 observations (years) in each broad education group (H and L) and we need to allow at least an education-specific time trend to capture the term $\ln\theta_{kt}$. This would not give enough degrees of freedom to estimate a parameter for each group allowing σ_{HH}, σ_{LL} and σ_{HL} to be different. Therefore, using the National Census Data the only possibility is to assume the (unverified) restriction that $\sigma_{HH} = \sigma_{LL} = \sigma_{HL} = \sigma_{EDU}$ so that equation (18) above reduces to:

$$\ln(\overline{W}_{kt}) = \ln\left(\alpha A_t^{\frac{1}{\alpha}} \kappa_t^{\frac{1-\alpha}{\alpha}}\right) + \frac{1}{\sigma_{EDU}}\ln(N_t) + \ln\theta_{kt} - \frac{1}{\sigma_{EDU}}\ln(N_{kt}) \tag{19}$$

Equation (19) allows the estimation of $\frac{1}{\sigma_{EDU}}$ using 24 observations (four education groups over six years) if we assume that the term $\ln\left(\alpha A_t^{\frac{1}{\alpha}} \kappa_t^{\frac{1-\alpha}{\alpha}}\right) + \frac{1}{\sigma_{EDU}}\ln(N_t)$ can be absorbed by a common time effect (or a common time-trend) and the education-specific productivity $\ln\theta_{kt}$ can be summarized in an education-specific time trend (plus possibly an education-specific fixed effect). By doing so we can estimate the following specification:

$$\ln(\overline{W}_{kt}) = I_t + (Time\ Trend)_k - \frac{1}{\sigma_{EDU}}\ln(\widehat{N}_{kt}) + e_{kt} \tag{20}$$

Conditional on these controls, the identifying assumption is that any other change in employment of foreign-

[20] The weight for the wage of each group equals the size of the composite input for that education-experience cell, L_{kjt}, relative to the size of the composite input for the whole education group L_{kt}. This is measured by the share of group k, j in total working hours of educational group k.

born within a group is a supply shift. The above one is the assumption made in Borjas (2003), Ottaviano and Peri (2006a) and Borjas and Katz (2007). It is impossible, due to the very few periods of observation in the Census data to test empirically the validity of the restriction $\sigma_{HH} = \sigma_{LL} = \sigma_{HL} = \sigma_{EDU}$. Moreover such restriction is neither common to the rest of the labor literature (that, as we illustrated above, mostly assumes $\sigma_{HH} = \sigma_{LL} = \infty$ and $\sigma_{HL} < \infty$) nor innocuous in determining the effects of immigration on wages (as we will show in section 6). It is very important, therefore, that we complement the current estimates with further data to produce independent estimates of σ_{LL} and σ_{HL}, that we do in the next section using CPS yearly data.

Table 5 shows the estimates of $-\frac{1}{\sigma_{EDU}}$ assuming the restriction $\sigma_{HH} = \sigma_{LL} = \sigma_{HL} = \sigma_{EDU}$ and implementing regression (20). If the elasticities $\frac{1}{\sigma_{HL}}$, $\frac{1}{\sigma_{LL}}$ and $\frac{1}{\sigma_{HH}}$ are not equal, such procedure would at best give an estimate of *their average value*. In this section we mostly care to show that even such average value is rather sensitive to the inclusion of few fixed effects, and in most cases our estimates of σ_{EDU} are a bit larger than (but comparable to) the one estimated and used in Borjas (2003) and Borjas and Katz (2007). The key point, however, made in the next section is that when we allow σ_{LL} and σ_{HH} to be different from σ_{HL} the data strongly suggest that those within-broad group elasticities are much larger than between-broad group elasticity and that σ_{LL} is close to ∞.

The difference between specification (1) and (2) in Table 5 is the construction of the aggregate labor input $\ln(\widehat{N}_{kt})$. In specification (1) we follow the model-based procedure described above and use the estimated elasticities σ_{IMMI} and σ_{EXP} to construct $\ln(\widehat{N}_{kt})$. In specification (2) we simply add hours worked across native and foreign workers and between different experience groups as if they were perfect substitutes. The estimated equation in column (1) and (2) is exactly as in expression (20) and the time effects I_t are assumed to be a common time trend while $(Time\ Trend)_k$ are education-specific time trends. The method of estimation is 2SLS using $\ln(F_{kt})$ the (logarithm of) hours supplied by foreign-born workers in education group k as instrument for $\ln(\widehat{N}_{kt})$. Specification (3) differs as it allows the common time effects I_t to be captured by dummies rather than by a trend while specification (4) adds to the time trends four education-specific dummies. Specification (1) and (2) reproduce the method adopted in Borjas (2003), Borjas and Katz (2007) and Ottaviano and Peri (2006a), specification (3) seems more consistent with the theoretical model as we have no reason to believe that the aggregate term $\ln\left(\alpha A_t^{\frac{1}{\alpha}} \kappa_t^{\frac{1-\alpha}{\alpha}}\right) + \frac{1}{\sigma_{EDU}} \ln(N_t)$ follows a trend in time, while specification (4) is a bit more demanding, as it assumes education-specific intercepts as well as time-trends to capture the terms $\ln \theta_{kt}$.

We estimate the elasticity $-\frac{1}{\sigma_{EDU}}$ on men only (first row), women only (second row), men and women pooled (third row) and, as in the previous tables, using employment rather than hours as alternative measure of labor input (fourth row) and omitting 1960 (fifth row). Most of the specifications in column (1) and (2) using the whole 1960-2006 sample produce estimates around -0.4, that imply $\sigma_{EDU} = 2.5$. Allowing a free time effect (column 3) or restricting the sample to post 1970, both cause a significant decline in the estimated value of

$\frac{1}{\sigma_{EDU}}$ that drops to 0.2 - 0.3 implying an elasticity σ_{EDU} between 3.3 and 5. Finally, including education effects (column 4) increases the estimates of $\frac{1}{\sigma_{EDU}}$ up to -0.7 but also dramatically increase their standard error so that the value is not significantly different from 0.

One needs to be careful when comparing these estimates to the previous literature. The only clear comparison is with Borjas (2003) that estimates $-\frac{1}{\sigma_{EDU}} = -0.759$ (standard error equal to 0.582) and Borjas and Katz (2007) who estimate $-\frac{1}{\sigma_{EDU}} = -0.412$ (with standard error equal to 0.312) as they use exactly the same model. The first point estimate is consistent with those in column (4) of Table 5, while the second is close to those in column (1) and (2). Our standard errors are smaller than those in the two previous studies, and the point estimates are similar to them. Hence our estimates of $-\frac{1}{\sigma_{EDU}}$ are as good as those produced by previous studies on the national impact of immigrants. Comparing these values, however, to the estimates of $\frac{1}{\sigma_{HL}}$ from the previous literature (such as Katz and Murphy, 1992; Angrist, 1995; Johnson, 1997; and Krusell et al, 2000) is very misleading. Those studies expressly estimate the elasticity between two groups (not four) with high and low education. They separate the groups at schooling level equal to high school graduation or some college education and expressly consider as perfect substitutes workers within each of the two groups. Hence, relative to that literature, the present method estimates an elasticity that averages the inverse $\frac{1}{\sigma_{HL}}$ (estimated mostly between 0.5 and 0.7) and $\frac{1}{\sigma_{HH}}$ and $\frac{1}{\sigma_{LL}}$ assumed equal to 0 in those studies. Interpreting $\frac{1}{\sigma_{EDU}}$ as such an average, values ranging between 0.24 and 0.44 as in our preferred specifications of Columns (1) and (2) of Table 5 are perfectly consistent with that literature. Our estimates of $\frac{1}{\sigma_{EDU}}$ provide no information, however, on the individual values of $\frac{1}{\sigma_{HL}}$, $\frac{1}{\sigma_{HH}}$ and $\frac{1}{\sigma_{LL}}$, nor do they test whether the equality restriction is upheld by the data. As there is no indication in the literature that those elasticities are equal, and as the actual value of $\frac{1}{\sigma_{LL}}$ is particularly relevant to calculate the wage effect of immigrants in the next section, we use the CPS yearly data to estimate independently $\frac{1}{\sigma_{HL}}$, $\frac{1}{\sigma_{HH}}$ and $\frac{1}{\sigma_{LL}}$ and test the restriction that they are equal.

5.3.2 Using the CPS and the Katz and Murphy Method

We implement the method used by Katz and Murphy (1992) (KM from now on) and described in section VI.A of their paper. The estimate of $\frac{1}{\sigma_{HL}}$ that they obtain is the most widely cited and used in this whole literature and therefore we think it is appropriate to take their data and method as natural reference and extend them to estimate $\frac{1}{\sigma_{HH}}$ and $\frac{1}{\sigma_{LL}}$. We use the yearly IPUMS-CPS data from King et al (2008) and we use a definition of the sample, of the education groups and of weekly wages, hours worked and other variables identical to those used for the Census data in the previous section.[21] The details for the construction of the sample and variables using the CPS data are in Appendix C. Essentially we consider workers 18 years or older not living in group quarters, who worked at least a week last year with experience between 1 and 40 years to construct the sample

[21] 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 (that we use in this section).

of hours worked (that measures labor inputs). And we use the same sample omitting self-employed and workers who did not receive wage compensation to construct the average weekly wages, weighting each individual by her hours worked. The data cover the period 1963-2006, so we have 44 yearly observations to estimate each elasticity. We first reproduce the exact KM method extending their analysis to the period 1963-2006 (their regressions only included the 1963-1987 period) and we run the following regression:

$$\ln(w_{Ht}/w_{Lt}) = I_t - \frac{1}{\sigma_{HL}} \ln(N_{Ht}/N_{Lt}) + u_t \tag{21}$$

The w_{Ht} is the average weekly wage of workers with college degree (calculated as hours-weighted average) and w_{Lt} is the hours-weighted average weekly wage of high school graduates. The KM method considers group H as made of college-equivalent labor units and L as constituted by high-school equivalent units. Hence the supply N_{Ht} is constructed including hours worked by college educated plus hours worked by those with some college weighted by 0.69 (the conversion factor between some college and college estimated by KM) while N_{Lt} includes hours worked by high school graduates plus those worker by people with no degree weighted by 0.93 and hours worked by people with some college weighted by 0.29.[22] Interpreting the term I_t as capturing the systematic component of the relative productivity $\ln(\theta_{Ht}/\theta_{Lt})$, and u_t as capturing its random component, equation (21) can be easily derived by taking the relative marginal productivity of N_{Ht} and N_{Lt} in our model. The only difference is that the nesting of our model implies that workers with some college should contribute their hours of work only to the construction of N_{Ht} (rather then being split between the two groups) as they are all included in group H. Finally following KM we consider the evolution of I_t over time as a time trend.

The first column of Table 6 shows the estimates of $-\frac{1}{\sigma_{HL}}$ implementing equation (21). We use the sample of men and women pooled in Table 6 (as done by KM) while we report in Table A5 in the Appendix the corresponding estimates using wages calculated on the male sample only. The difference between the first and the second row is in the split of hours worked by those with some college education. In the first row we split them between the two groups (as described above and exactly reproducing KM) and in the second we include them in the group H only, more consistently with out model. The third row uses employment rather than hours worked as measure of labor supply and the last row omits the Sixties. We report in brackets the OLS standard errors and in square brackets the Newey-West autocorrelation-robust standard errors (as the time-series data may contain some autocorrelation).

The estimates of $-\frac{1}{\sigma_{HL}}$ obtained with the KM method extended to the 1963-2006 (or 1970-2006) period are between -0.52 and -0.66, with standard errors between 0.06 and 0.09 hence very significantly different from 0. They are close to the original estimates -0.709 with standard error of 0.15 and confirm the imperfect substitution

[22] For the justification of thse weights see Katz and Murphy (1992) page 68. The results are essentially identical weighting workers with no degree by 1 in the group L and splitting workers with some college 50-50 between the H and the L group.

between workers in the H and in the L group with an elasticity ranging between 1.5 and 1.8. The estimate obtained including workers with some college in H only (second row) is somewhat smaller -0.32, and compatible with an elasticity between 2 and 3. All in all those estimates confirm that an elasticity around 2, which has been frequently used in the literature, seems a reasonable estimate of σ_{HL}.

The KM method and our nested structure, moreover, allow us to estimate on the time series data also the elasticities $\frac{1}{\sigma_{HH}}$ and $\frac{1}{\sigma_{LL}}$ in particular from expressions (3) and (4) of our model we can derive the following two estimating equations:

$$\ln(w_{HSGt}/w_{SHSt}) = I_{Lt} - \frac{1}{\sigma_{LL}} \ln(N_{HSGt}/N_{SHSt}) + u_{Lt} \tag{22}$$

$$\ln(w_{COGt}/w_{SCOt}) = I_{Ht} - \frac{1}{\sigma_{HH}} \ln(N_{COGt}/N_{CODt}) + u_t \tag{23}$$

Equation (22) is used to estimate $\frac{1}{\sigma_{LL}}$ by regressing the relative weekly wages of high school graduates relative to workers with no degree on their relative hours worked, assuming that I_{Lt} (that captures $\ln(\theta_{HSGt}/\theta_{SHSt})$) follows a time-trend, while (23) is used to estimate $\frac{1}{\sigma_{HH}}$ by regressing the relative weekly wages of college graduates relative to those with some college on their relative hours worked, also assuming that I_{Ht} (that captures $\ln(\theta_{COGt}/\theta_{SCOt})$) follows a time trend. Column 2 and 3 of Table 6 report the estimates of $-\frac{1}{\sigma_{LL}}$ and $-\frac{1}{\sigma_{HH}}$ respectively. Column 2 and 3 of Table A5 report the same estimates for the sample of men only. The most important result emerging very consistently from those estimates is that both of them, and particularly $-\frac{1}{\sigma_{LL}}$, are much smaller in absolute value than $-\frac{1}{\sigma_{HL}}$. In the majority of cases $-\frac{1}{\sigma_{LL}}$ and $-\frac{1}{\sigma_{HH}}$ are not significantly different from 0. The estimates of $-\frac{1}{\sigma_{LL}}$ 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 of the hypothesis $-\frac{1}{\sigma_{LL}}$ =-0.32 (the lowest estimate of $-\frac{1}{\sigma_{HL}}$) is 258, rejecting the null of equality at an overwhelming level of confidence. The estimate of $-\frac{1}{\sigma_{HH}}$ is around -0.10, and also a one-sided test always reject the hypothesis that it is equal to -0.32.

Hence the two crucial results emerging from Table 6 (and 5A) are the following. First, the restriction $\frac{1}{\sigma_{HL}} = \frac{1}{\sigma_{HH}} = \frac{1}{\sigma_{LL}}$ is overwhelmingly rejected by the data. Second the estimated value of $\frac{1}{\sigma_{LL}}$ 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. The value of $\frac{1}{\sigma_{HH}}$ is estimated around 0.10, also much smaller than $\frac{1}{\sigma_{HL}}$, often not significantly different from 0, implying an elasticity of 10 or larger.

The method used above to estimate those crucial elasticities does not hinge on variation of supply generated by immigration. The CPS data do not allow us to measure hours variation due to immigrants as they begin recording immigration status in 1994 leaving 12 observations only. However, the CPS begins recording "Hispanic

Origin" status from 1970. Hence assuming that changes in Hispanic workers among less educated are mainly due to immigration we can re-estimate (22) on post 1970 data (37 observations) instrumenting N_{HSGt}/N_{SHSt} with the equivalent measure of relative hours worked by Hispanics only. The point estimate of $-\frac{1}{\sigma_{LL}}$ (not in the Table) using this method is -0.019 and the standard error is 0.035. Again no evidence of imperfect substitution is found.

All in all, the last two sections produce very robust evidence that is consistent with the previous labor literature that leads us to the following assessment relative to the parameters $\frac{1}{\sigma_{HL}}$, $\frac{1}{\sigma_{HH}}$ and $\frac{1}{\sigma_{LL}}$. While imposing the equality restriction used first by Borjas (2003) and then by Ottaviano and Peri (2006a) and Borjas and Katz (2007) generates estimates of $\frac{1}{\sigma_{EDU}}$ around 0.40, that value can at most be interpreted as an average of those elasticities. However, using CPS data we find that the equality restriction its overwhelmingly rejected by the data. The same data suggest that reasonable estimates for individual elasticities are in the range between 0.5 and 0.66 for $\frac{1}{\sigma_{HL}}$ and between 0 and 0.10 for $\frac{1}{\sigma_{HH}}$ and $\frac{1}{\sigma_{LL}}$ with the first coefficient closer to 0.10 and the second closer to 0. The estimated value of $\frac{1}{\sigma_{EDU}}$ around 0.40 is indeed between those estimates, compatible with the idea that it somehow estimates an average between them.

6 Immigration and Wages: 1990-2006

We are now ready for the third and final step in calculating the effects of immigration on the wages of U.S.- and foreign-born workers. The first step of the procedure (Section 3) required specifying a production function and deriving labor demand curves and the elasticity of wages with respect to immigration of workers with different skills. The second step (Section 5) required estimation of the relevant parameters (elasticities of substitution). The third step (this section) uses these estimates and the actual flow of immigrants by group during the 1990-2006 period (reported in column 3 of Table 1) in the expressions reported in Appendix A to calculate the effects of immigrants on the wages of U.S.- and foreign-born workers in individual groups as well as overall.

6.1 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 the partial elasticity of native wages to immigration within the same skill group (often taken as an education-experience group) and treat this elasticity as "the effect of immigration on wages".[23] As we illustrated in Section 3.3, the partial effect, described in equation (12), is uninformative of the actual overall effect of immigration on wages. To evaluate that we need to consider the entire distribution of immigrants across skill

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

groups, the cross effects among groups and the adjustment of capital. More importantly, the partial elasticity (12) is likely to be negative in most reasonable models as long as immigrants are closer substitutes for natives in the same group (education-experience) than they are to natives in other skill groups.

For instance, using estimates from Tables 2 and 4, the term $\left(\frac{1}{\sigma_{IMMI}} - \frac{1}{\sigma_{EXP}}\right)$ is calculated to be negative and around -0.10 (since the preferred estimate of $\frac{1}{\sigma_{IMMI}}$ is around 0.05 and the preferred estimates of $\frac{1}{\sigma_{EXP}}$ are around 0.15). This is a partial elasticity and can be interpreted, using formula (12) as meaning that an increase by 10% in the hours supplied in group k, j, given constant supply in the other groups (i.e., keeping fixed the aggregates N_{kt} and N_t) would produce a negative 1% variation in the real wage of native workers in the group. If one fails to notice the *partial* nature of the elasticity above, one could be tempted to generalize these findings, interpreting them as saying that the inflow of immigrants over the period 1990-2006, which increased total hours worked by 11.4%, caused a negative 1.1% change (over 1990-2006) in the average wages of natives ($0.10 * 11.4\%$), or that groups such as high school dropouts, for which the inflow of immigrants was as high as 23% of initial hours worked, lost as much as 2.3% of their wage. Such a simplistic generalization is misleading, however, as expression (12) only accounts for the effect on wages of immigrants in the same skill group and omits all the cross-group effects from immigrants in other skill groups, many of which are positive effects. In fact (as we see in Section 6.2 below), while sharing the same negative partial elasticity $\left(\frac{1}{\sigma_{IMMI}} - \frac{1}{\sigma_{EXP}}\right)$, the wage effects on natives across groups were very different: some were positive and others negative, depending on the relative size of the skill groups, the relative strength of cross-group effects and the actual pattern of immigration across groups. The simplistic values of -1.1% or -2.3% mentioned above do not bear any resemblance to the actual wage effects calculated below, which differ across education groups and depend on the elasticity and supply in each group. Limiting our attention to the elasticity $\varepsilon_{kjt}^{partial}$, or emphasizing this effect too much, would be misleading in evaluating the effect of immigration on wages.

6.2 Long Run Effects of Immigration on Wages

The results in Table 7 are some of the most important in the paper. These simulation results describe the impact of immigration over the 1990-2006 period on the wages of U.S.- and foreign-born workers in the long run. We focus on the 1990-2006 period as it is the most recent covered by available Census and ACS data and it is the period of greatest immigration in recent U.S. history. To obtain the simulated effects we proceed in four steps. First, using expressions (25) and (26) in Appendix A, the relevant parameter values σ_{IMMI}, $\sigma_{EXP}, \sigma_{HL}, \sigma_{HH}$ and σ_{LL} as well as the percentage change in foreign-born workers by skill group, $\Delta F_{kj,1990-2006}/\ F_{kj,1990}$ (shown in Table 1) we calculate the percentage change in real wages for U.S.-born and foreign-born workers in each skill group (k, j). The value of the elasticities used in each simulation are reported in the first five rows of Table 7. Second, we obtain the average wage change in each education group for foreign- and U.S.-born workers by weighting the percentage change of each experience sub-group by its wage share in the education group. This provides the entries in the rows labelled "less than HS" , "HS graduates", "Some CO" and "CO graduates" in Table 7. Third, we average the changes across education groups for U.S.- and foreign-born separately, again weighting them by their wage shares as described in formulas (27) and (28) in Appendix A. Those values are reported in the rows labelled "Average US-born" and "Average Foreign-Born". Finally, we average the changes for the two groups (U.S.- and foreign-born workers), still using wage-share weights (as described in formula (29) in Appendix A), to obtain the overall wage change reported in the last row labelled "Overall Average". The upper part of Table 7 can be compared to the results obtained in the previous literature (Borjas, 2003 and Borjas and Katz, 2007) that mostly focuses on the effect of immigration on the wages of U.S.-born workers. The lower part of Table 7 reports the effects of immigration on the wages of foreign-born, less frequently considered in the previous literature. The table reports the "long run" effects, namely the wage effects once capital has fully adjusted, $(\Delta\kappa_t/\kappa_t)_{immigration} = 0$.[24]

In order to evaluate how our simulation fits with the previous labor literature the first three columns present the simulated wage effect of immigrants using the most common elasticity estimates from the literature. As argued above, it is common in the labor and macro literature to adopt a value of σ_{HL} between 1.5 and 2 (following Katz and Murphy, 1992; Johnson, 1997; Autor, Katz and Krueger, 1998; Krusell et al., 2000 and others). It is also common to consider workers with some college and a college education (within H) as perfect substitutes as well as for workers with no degree and with a high school degree within L, hence $\sigma_{LL} = \sigma_{HH} = \infty$. From Card and Lemieux (2001) and Welch (1979) we borrow a value of σ_{EXP} between 3.3 and 10. Finally we assume perfect substitution between immigrants and natives in a cell, $\sigma_{IMMI} = \infty$. Column 1 uses values of elasticity in the low end of the range from the literature, column 2 uses values in the high end and column 3 chooses a typical median value. The wage effects of column (3) would therefore be what the"median economist" would predict without re-estimating the elasticity of demand using the immigration shocks. As we see, the simulated effects imply a very modest negative wage effect for native workers with no degree (-0.5%) as well as for those with a high school degree (-0.3%), and a modest positive wage effect for workers with some college or more ($+0.1\%$).

Before looking at the intermediate columns which use our own estimates, let us compare those effects with those estimated in Borjas and Katz (2007), shown in the last column in Table 7. It is evident that the restriction $\sigma_{HL} = \sigma_{LL} = \sigma_{HH} = 2.4$ (rejected by the data) is responsible for generating the large negative impact (-4.7%) on the group of natives with no degree, estimated in that article. That restriction is also responsible for generating the significant negative effect on college graduates (-1.6%). Plainly stated, while immigration over 1990-2006 was rather unbalanced, especially between workers with no high school degree (+23.6% labor supply

[24] Notice that, by assumption of constant return to scale (in K and N) in the production function, and because we assume no effect of immigration on technology, the overall average wage effects in the long-run has to be 0.

due to immigrants) and high school graduates (+10% due to immigrants), it was rather balanced between workers with high school or less (+13% of labor supply) and those with some college or more (+10%). The elasticity value σ_{LL} plays a fundamental role in determining the relative wage effects, and a value as low as 2.4 (used by Borjas and Katz, 2007) produces dramatic effects relative to our estimated value of 20 (see below) or to the routinely assumed value of ∞ (closer to 20, and in fact producing an almost identical effect to that obtained using an estimate of 20) used in columns 1-3. Those large negative effects, therefore, contrast with what one would predict using parameters previously estimated.

What do the parameter estimates of σ_{IMMI}, the only parameter specific to the immigration literature, add to a model that otherwise uses standard estimates from the labor literature? Columns 4 to 6 illustrate such an effect. While the degree of imperfect substitution between natives and immigrants is small (σ_{IMMI} is between 15 and 30, and most likely around 20), it is enough to generate non-trivial differences, particularly on the wage of the group with no degree and on the wage of foreign-born workers. For instance, column 6 uses the typical estimate of $\sigma_{IMMI} = 20$ and shows, relative to column 3 (with identical parameters and $\sigma_{IMMI} = \infty$) that less educated natives now experience a small, real wage gain (+0.7%) rather than a small loss (-0.5%) and, similarly, college graduates increase their gain to 0.9% (up from 0.1%). These differences of 0.8-1.0%, while not as large as those between columns 3 and 10, contribute to producing an even less pessimistic assessment of the effect of immigration on native wages. The small real wage gains of natives in column 6 relative to 3 happen, obviously, at the expense of previous immigrants who bear most of the direct competition effect of new immigrants (as our model assumes that they are perfect substitutes with them) and lose, in our median estimates of column 6, between 4.5 and 7.5% of their wage. This is the relevant distributional shift due to immigrants: all native workers gain (a little) from immigrants and all previous immigrants lose (a non-trivial amount) from new immigration. On average, natives gain 0.6% of their wages from immigration because the imperfect substitutability of immigrants allows them to appropriate a larger part of the immigration surplus, at the expense of previous immigrants who lose 6.4% of their real wages.

Finally, columns 7 to 9 repeat the simulations using the range of parameters estimated in this paper. The main departure from the results of columns 4 to 6 is that the elasticities σ_{HL}, σ_{LL} and σ_{HH} are now estimated using the CPS data. However, since σ_{LL} and σ_{HH} are quite large (between 10 and 50) and our estimates of σ_{HL} are close to those in the literature (between 1.4 and 2), the simulations in columns 7-9 are remarkably close to those in 4-6. They are also not very different from those in 1-3 but are significantly different from those of Borjas and Katz (2007) in column 10. In our typical estimate (column 9) natives with no degree actually experience a very small gain (+0.3%) since their mild imperfect substitutability with immigrants compensates for the small negative effect (-0.5%) caused by the relative abundance of immigrants in the group L. Still, in relative terms workers with some college or a college degree gain the most in our preferred simulation (+1.0%

and +0.5%, respectively). What is remarkable, however, is that even with the smallest value of σ_{LL}, which is compatible with our estimates (in Section 5.3.2) the group of less educated natives loses at most 0.3% of its real wage as the result of 16 years worth of immigrant inflows, and the other groups gain, in the long run, between 0.4% and 1%.

In summary, while very different from those presented in Borjas and Katz (2007), our estimated effects for native workers are extremely similar to those produced by simply applying the most common elasticity estimates available in the labor literature to the immigration-driven labor supply shock. The only difference is due to the fact that our explicit estimate of a small degree of imperfect substitution between natives and immigrants produces a small, positive wage effect on all natives and a significant, negative wage effect on previous immigrants.

6.3 Short Run Effects with Yearly Capital Adjustment

How long does it take for physical capital to adjust and restore its long run returns? And in the presence of sluggish adjustment of capital what are the effects of immigration on wages in the short run? As discussed in Section 3.3 (and shown in Appendix A), accounting for capital adjustment simply adds a non-zero term, $(1-\alpha)\left(\frac{\Delta\kappa_t}{\kappa_t}\right)_{immigration}$, to the change in the wage of each group. Hence, the short run wage response for each group and for the averages will differ from the long run response by a common constant, due to the chosen Cobb-Douglas structure in which κ_t only affects marginal productivity of workers through the overall average wage. A popular way to analyze the deviation of $\ln(\kappa_t)$ from its balanced growth path trend, used in the growth and business cycle literature, is to represent its time-dynamics in the following way:

$$\ln(\kappa_t) = \beta_0 + \beta_1 \ln(\kappa_{t-1}) + \beta_2(trend) + \gamma\frac{\Delta F_t}{L_t} + \varepsilon_t \tag{24}$$

where the term $\beta_2(trend)$ captures the balanced growth path trajectory of $\ln(\kappa_t)$, equal to $\frac{1}{\alpha}\ln\left(\frac{1-\alpha}{r+\delta}A_t\right)$, and the term $\beta_1\ln(\kappa_{t-1})$ captures the sluggishness of yearly adjustment to shocks. The parameter $(1-\beta_1)$ is commonly called the "speed of adjustment " since it is the share of the deviation from the balanced growth path (trend) eliminated each year. Finally, $\frac{\Delta F_t}{L_t}$ are the yearly immigration shocks and ε_t are other shocks. Assuming that immigration shocks cause a proportional decrease in κ_t in each year, in order to calculate the effect of immigration on κ_t over, say, the 1990-2006 period, one needs an estimate of the parameter β_1. Once we know β_1 and the sequence of yearly immigration flows, $\frac{\Delta F_t}{L_t}$, one can use (24) to obtain an impulse response of $\ln(\kappa_t)$ and its deviation from trend as of 2007 (short run), as well as for later years (medium and long run). The previous migration literature has essentially assumed $\beta_1 = 0$ in the short run calculations, aggregating the $\frac{\Delta F_t}{L_t}$ over one or two decades assuming fixed capital stock (implying a very large deviation from the trend!). On the other hand, it has assumed $\beta_1 = 1$, (full adjustment) in the long run calculations. The recent empirical growth literature (Islam, 1995; Caselli et al., 1996) and the recent business cycle literature (Romer, 2006, Chapter 4), in contrast, provide model-based and empirical estimates of β_1. The recent growth literature usually estimates a 10% speed of convergence of capital to the own balanced growth path for advanced (OECD) economies (Islam, 1995; Caselli et al., 1996), implying $\beta_1 = 0.9$. Similarly, the business cycle literature calculates the speed of convergence of capital to be between 10% and 20% in each year (Romer, 2006, Chapter 4) for closed economies, and even faster rates for open economies. Hence $\beta_1 = 0.9$ seems a reasonable estimate (if anything on the conservative side). We also estimated a simple AR(1) process with trend for $\ln(\kappa_t)$. We constructed the variable $\kappa_t = (K_t/L_t)$, dividing the stock of U.S. capital at constant prices (Net Stock of Private and Government Fixed Assets from the Bureau of Economic Analysis, 2008) by the total non-farm employment from the Bureau of Labor Statistics (2008) for each year during the period 1960-2006. We estimated several specifications including changes in total employment as a shock$\left(\frac{\Delta L_t}{L_t}\right)$, or immigrants only $\left(\frac{\Delta F_t}{L_t}\right)$ as a shock and instrumented those with changes in the population (to correct for endogeneity of employment).[25]

All estimates of β_1 ranged between 0.8 and 0.9 (a speed of adjustment of 10 to 20% a year) with standard errors ranging between 0.02 and 0.08. We could never reject $\beta_1 = 0.9$, and we could always reject $\beta_1 = 1$ (no adjustment). Hence we consider 10% a reliable estimate of the yearly speed of capital adjustment. Using the series of immigration rates over 1990-2006 and the estimated parameters of capital adjustment $\beta_1 = 0.9, \gamma = -0.9$ (assuming that capital adjustment begins the same year as immigrants are received), the recursive equation (24) allows us to calculate $(\Delta\kappa_{1990-2006}/\kappa_{1990})_{immigration}$ as of year 2007 and the share of the deviation from trend that remains five years (medium run) later in 2012. Using formula (9) we can calculate the effect of $\Delta\kappa$ on the average wage and on each group's wage. To the contrary, assuming no adjustment of capital in the short run ($\beta_1 = 1, \gamma = -1$), since the cumulated inflow of immigrants during the 1990-2006 period amounts to 9.6% of the total hours worked in 1990[26], implies an effect of immigration on average real wages equal to $(0.33) * (-9.6\%) = -3.2\%$, as of 2007. Using the actual 10% speed of adjustment of capital each year, however, we obtain an effect on the capital-labor ratio due to immigration of just -3.5%, corresponding to a mere -1.1% $(= 0.33 * 3.5\%)$ effect on real wages as of 2007, and in five more years (2012) the negative effect on wages is reduced to -0.6%.

Table 8 reports the simulated effects on wages as of 2007 (column 1) and as of 2012 (column 2). The values are calculated accounting for the yearly (short run) capital adjustment described above in response to the yearly inflow of immigrants up to 2006. We use the parameter values as in column 9 of Table 7 (which represents our preferred specification). In the first column of Table 8 we show the wage effect as of 2007, and in the second we

[25] We constructed ΔF_t, for each year from 1960 to 2006, using the following procedure. From the U.S. Department of Justice, Immigration and Naturalization Service we obtained the number of (legal) immigrants for each fiscal year 1960-2006. We then distribute the net change of foreign-born workers in each decade (measured from Census data and from the American Community Survey, which includes illegal immigrants as well as legal ones) over each year in proportion to the gross yearly flows of legal immigrants.

[26] This number is a bit smaller than the 11% in Table 1 because here we cumulate yearly percentage changes, using the beginning of each year as the initial value, while in Table 1 we expresse the total 1990-2006 changes as a percentage of 1990 values.

show the effect as of 2012 assuming no immigration between 2007 and 2012. This gives us an idea of the speed at which the economy converges to the long run effects (column 3). As a comparison, column 4 shows the wage effect obtained with the traditional method of keeping capital fixed (over 16 years), thus allowing a very large decrease in the capital-labor ratio between 1990 and 2006, while column 5 shows the wage effects obtained using the traditional short run method (fixed capital) and the parameter values as in column 10 of Table 7– that is, it shows the effects of immigration over 1990-2006 obtained using the Borjas and Katz (2007) method for the short run effect, corresponding also to the method used in Borjas (2003).

Three features are worthy of notice and comment. First, there is a significant difference in the effects on native wages between our method, which accounts for the short run adjustment of capital, and the traditional method with fixed capital. Not accounting for short run capital adjustments produces a negative effect on wages of all natives around 2.1% (the difference between values in column 1 and column 4). Second, cumulating the over-estimate of the negative effect on less educated workers due to the assumption $\sigma_{HL},=\sigma_{LL} = \sigma_{HH}$ and the negative effect of the traditional short run treatment of capital, the estimates obtained following the Borjas and Katz (2007) method, reported in column 5, show a -7.8% effect on wages of workers with no degree. This is one order of magnitude larger than our estimated short run effect (-0.7%). Finally, one sees that after only 5 years about 40% of the distance between the short run effects and long run effects has been eliminated, with the average wage effect on natives equal to 0% (up from -0.4% in 2007) and moving towards the long run effect of +0.6%. Given the estimated speed of capital adjustment, the inter-census changes (10 years) are better approximated by the long run effects than by the short run effects. The negative short run effects for old immigrants range between -6% and -9%, because this group is the one experiencing most of the competition from new immigrants.

All in all, our preferred estimates indicate that immigration had a small negative impact in the short run on natives with a high school degree or less (on the order of -0.6 to -0.7%), but in the long run the effect on these groups was a small gain (+0.3 to +0.4%). In any case the effects are small and explain very little of the difference in performance of wages between workers with a college degree and those with a high school degree or less over the 1990-2006 period. Just to give an idea of the inability of immigration to explain wage performances in the 1990-2006 period, let us consider the wage change of workers with no degree (-2.6% in real terms) and the wage change of those with college or more (+9.6% in real terms) that are reported in Table 1. Of the 12.2 percentage point difference in growth between the two groups (obtained by subtracting the first value from the second) our preferred specification (column 9 of table 7) implies that only 0.2 percentage points (=0.5%-0.3%) can be explained by immigration. The typical estimate from a standard labor model (column 3 of Table 7) would imply that 0.6 percentage points are explained by immigration. In either case less than one twentieth of the total difference can be explained by immigration. Immigration explains *even less* if we consider the wage differential between workers with high school or less and those with college or more. Over the 1990-2006 period the first group had a decline of 1.5% and the second an increase of 9.6%, for a difference of 11.4 percentage points. Again, the simulations of Table 7 imply a differential in wage performance due to immigration of 0.15% for our preferred estimate and of 0.5% for the traditional labor estimates. While we may still be worried by a 0.5% effect over 16 years it does not even come close to explaining the almost 12 percentage point differential in growth between workers with a high school degree or less and college graduates.

6.4 Comparison with cross-city estimates

We have already emphasized above that the estimates and simulations presented in this paper are perfectly in line, in method and values, with a long tradition in the labor literature that estimates the elasticity of substitution between workers of different skills and determines the impact of demand and supply shocks on wages (from Katz and Murphy, 1992, to Autor, Katz and Krueger, 1998, to Card and Lemieux, 2001). We want to argue here that our results also go in the direction of reconciling the apparent puzzle in the estimates of immigration effects at the local and at the national level.

As mentioned earlier, several studies on the relative wage effects of immigrants using local data (e.g., for metropolitan areas) typically find a small negative relative effect of immigrants on wages even when accounting for the internal migration response of U.S. natives (Card, 2001; Card and DiNardo, 2000; Lewis, 2005) and correcting for the endogeneity of the immigrant's choice of location (both factors would cause an attenuation bias in the estimates). In light of the present model and results, those small effects are not surprising at all. Immigrants at levels of education lower than high school compete imperfectly with the large group of natives with a high school degree or less. Moreover, their inflow is rather balanced, in most cities, between this group and the group of college graduates. Most of the states that attracted many low skilled migrants such as California, New York, Texas, and Illinois also attracted a large group of highly educated workers.[27] While immigrants are a disproportionate share of workers with no degree, if we merge them with high school graduates their inflow in the last decade was not much larger than the inflow of immigrants among college graduates, in most states and cities, as a percentage of their respective group. Such a pattern of supply would produce small relative effects in light of our elasticity estimates. For instance, the small elasticities estimated in Table 6.7 of Card and Lewis (2007), implying that an increase of 10% in the relative supply of high school dropouts (due to immigrant inflows) would decrease their wage by 0.3-0.5% *relative to high school graduates,* is perfectly in line with the estimates of $1/\sigma_{LL}$ (=0.04) in Section 5.3.2 above. Similarly, the small relative effects (between -0.03 and -0.10) of immigration on the wage of quartile 1 relative to quartile 2 for natives estimated in Table 7 of Card (2007) is in line with the estimates of $1/\sigma_{LL}$ between 0.03 and 0.10 as long as we interpret the two

[27]The most notable exception is Arizona, a state that attracted mostly immigrants with a high school degree or less over the 1990-2006 period.

quartiles as mostly containing workers with a high school education or less. Certainly the possibility that natives use other mechanisms to protect their wages from immigration (such as mobility across states, or changes in specialization) may still be important, and this is worth analyzing.

A second interesting phenomenon emerging from the city and state analysis (e.g., in our recent work, Ottaviano and Peri, 2005, 2006b, 2007 and recent work by Card, 2007) points to a positive and significant effect of immigration on the *average wage* of U.S. natives across U.S. states and metropolitan areas. This positive and significant effect survives 2SLS estimation, using instruments that should be exogenous to city-specific, unobservable productivity shocks. While the imperfect substitution estimated in this paper can go part way to explaining the positive effects on average native wages, the magnitude of estimates at the city level is much bigger than the small positive effect estimated here. In fact, our model predicts an increase in the wage of natives of 0.5% for an increase in labor supply due to immigrants of 10%, while typical city-level estimates imply average wage increases of $2 - 2.5\%$. It is possible that improved efficiency, gains from specialization, and improved technological adoption have a part in explaining those local average effects. While the effect of immigration on productivity is the next item in our research agenda, in this paper we have ruled out any effect of immigration on technology, efficiency or productivity, and in this respect we have taken a rather conservative approach.

7 Conclusions

The present paper adopts the "national approach" to the analysis the effect of immigration on wages in the tradition of Borjas (2003), Borjas and Katz (2007) and Ottaviano and Peri (2006a). In the process it clarifies four fundamental points.

First, a structural model of production that combines workers of different skills as well as capital, and furthermore estimates their elasticities of substitution, is necessary to assess the effect of immigration on the wages of native workers of different skills. Estimating a reduced form or a partial elasticity cannot possibly be informative of the total effect of immigration as this derives not only from the direct competition but also from the indirect complementarities of immigrants.

Second a crucial parameter in determining the effect of immigrants is the elasticity of substitution between workers with no degree and workers with a high school degree. This paper demonstrates that the long-established tradition in labor economics (but overlooked by Borjas, 2003, Borjas and Katz, 2007 and Ottaviano and Peri, 2006a) of assuming that this elasticity is infinite is strongly supported by the data. While the elasticity between workers with some college education or more and those with high school education or less is much smaller (equal to 2), the balanced inflow of immigrants belonging to these two groups implies very small relative wage effects of immigration, and a very small negative impact on wages of less educated immigrants.

Third, there seems to be a small but significant degree of imperfect substitution between natives and immigrants within education-experience groups. An elasticity of 20 is strongly supported by our estimates. This cannot be ruled out even by the extremely conservative method of Borjas, Grogger and Hanson (2008). For immigration to the US between 1990 and 2006, it implies an average positive long-run effect on native wages equal to +0.6% and an average negative effect on the wages of previous immigrants of about -6%.

Fourth, accounting for capital adjustment, the negative effect of immigration on wages is modest even in the short run: −0.7% for workers with no high school degree as of 2007. This represents a substantial revision of the previous short-run effects calculated using the Borjas and Katz (2007) method that would be for the 1990-2006 period equal to around −7.8% or workers with no high school degree. Such a large discrepancy is mainly due to their unwarranted assumptions of a fixed capital stock and a small elasticity of substitution between workers with no degree and those with a high school degree (around 2.4).

In sum, this paper reconciles the estimates and the findings of the national approach to the effects of immigration on wages with most of the estimates of the substitutability across workers of different skills produced by the labor literature in the last fifteen years. It also reconciles the aggregate evidence on the wage effects of immigrants with the evidence from the "area approach" which has always found small effects across US cities. In this respect, we hope that our modeling strategy as well as our estimates and simulations can provide a unified reference point for the current and future debate on the wage-effects of immigration in the US.

References

Acemoglu, Daron. 2002. Directed Technical Change. *Review of Economic Studies*, 69(4), pp. 781-810.

Angrist, Joshua. 1995. The Economic Returns to Schooling in the West Bank and Gaza Strip. *American Economic Review* 85, no. 5:1065-1087.

Autor, David, Lawrence Katz, and Alan Krueger (1998) "Computing Inequality: Have Computers Changed The Labor Market?," *The Quarterly Journal of Economics*, MIT Press, vol. 113(4), 1169-1213.

Bureau of Economic Analysis. 2008. Interactive NIPA Tables and Interactive Fixed Assets Tables. http://www.bea.gov/bea/dn/home/gdp.htm.

Bureau of Labor Statistics. 2008. National Employment Data. http://www.bls.gov/bls/employment.htm.

Borjas, George. 1994. The Economics of Immigration. *Journal of Economic Literature* 32, no. 4:1667-1717.

Borjas, George. 1999. Heaven's Door. Princeton University Press, Princeton and Oxford, 1999.

Borjas, George. 2003. The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market. *Quarterly Journal of Economics* 118, no. 4: 1335-1374.

Borjas, George. 2006. Native Internal Migration and the Labor Market Impact of Immigration. *Journal of Human Resources* 41, no.2: 221-258.

Borjas, George, and Lawrence Katz. 2007. The Evolution of the Mexican-Born Workforce in the United States. in Borjas, George, editor "*Mexican Immigration to the United States*" National Bureau of Economic Research Conference Report, Cambridge Ma.

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

Borjas, George, Richard Freeman, and Larry Katz. 1997. How Much Do Immigration and Trade Affect Labor Market Outcomes?. *Brookings Papers on Economic Activity* 1997, no1: 1-90

Butcher, Katrin and David Card. 1991. Immigration and Wages: Evidence from the 1980s. *American Economic Review Papers and Proceedings* 81, no. 2: 292-296.

Card, David. 1990. The Impact of the Mariel Boatlift on the Miami Labor Market. *Industrial and Labor Relation Review* 43, no 2: 245-257.

Card, David. 2001. Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics* 19, no 1: 22-64.

Card, David. 2007. How Immigration Affects U.S. Cities. CReAM Discussion Paper, no. 11/07.

Card, David, and John DiNardo. 2000. Do Immigrant Inflows Lead to Native Outflows? NBER Working Paper, no. 7578, Cambridge, Ma.

Card, David, and Thomas Lemieux. 2001. Can Falling Supply Explain the Rising Returns to College for Younger Men? A Cohort Based Analysis. *Quarterly Journal of Economics* 116, no.2: 705-746.

Card, David, and Ethan Lewis. 2007. The Diffusion of Mexican Immigrants During the 1990s: Explanations and Impacts. in Borjas, George , editor *Mexican Immigration to the United States*. National Bureau of Economic Research Conference Report, Cambridge Ma.

Caselli, Francesco, Gerardo Esquivel, and Fernando Lefort. 1996. Reopening the Convergence Debate; A New Look at Cross-Country Growth Empirics. *Journal of Economic Growth* 1, no.3: 363-389.

Caselli, Francesco, and Wilbur Coleman. 2006. The World Technology Frontier. *American Economic Review* 96, no.3: 499-522.

Cortes, Patricia. 2006. The Effect of Low-Skilled Immigration on U.S. Prices: Evidence from CPI Data. Manuscript. Massachusetts Institute of Technology, Cambridge, MA.

D'Amuri, Francesco, Gianmarco Ottaviano, and Giovanni Peri. 2008. The Labor Market Impact of Immigration in Western Germany in the 1990's. FEEM Working Paper No. 16, 2008.

Felbermayr G., W. Geis, W. Kohler. 2008. Restrictive Immigration Policy in Germany: pains and Gains Foregone? Manuscript University of Tubingen, April 2008.

Friedberg, Rachel, and Jennifer Hunt. 1995. The Impact of Immigrants on Host Country Wages, Employment and Growth. *Journal of Economic Perspectives* 9, no. 2: 23-44.

Friedberg, Rachel. 2001. The Impact of Mass Migration on the Israeli Labor Market. *Quarterly Journal of Economics* 116, no. 4: 1373-1408.

Gollin, Douglas. 2002. Getting Income Shares Right. *Journal of Political Economy* 100, no 2: 458-474.

Grossman, Jean B. 1982. The Substitutability of Natives and Immigrants in Production. *Review of Economics and Statistics* 64, no.4: 596-603.

Islam, Nasrul. 1995. Growth Empirics: A Panel Data Approach. *Quarterly Journal of Economics* 110, no.4: 1127-1170.

Jaeger, David. 1996. Skill Differences and the Effect of Immigrants on the Wages of Natives. U.S. Bureau of Labor Statistics, Economic Working Paper no.273. Washington D.C.

Johnson, George E. 1997. Changes in Earnings Inequality: The Role of Demand Shifts. *The Journal of Economic Perspectives* 11, no. 2: pp. 41-54

Jones, Charles. 2005. The Shape of Production Functions and the Direction of Technical Change. *Quarterly Journal of Economics* 120, no2: 517-549.

Kaldor, Nicholas. 1961. Capital Accumulation and Economic Growth in the Theory of Capital. F. A. Lutz and D.C. Hague Editors. New York, St. Martins.

Katz, Larry, and Kevin Murphy. 1992. Changes in Relative Wages 1963-1987: Supply and Demand Factors. *Quarterly Journal of Economics* 107, no.1: 35-78.

Ruggles, Steven , Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander. 2008. *Integrated Public Use Microdata Series*: Version 3.0 [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor]. http://www.ipums.org.

Krusell, Per, Lee Ohanian, Victor Rios-Rull and Giovanni Violante. 2000. Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica* 68, no. 5: 1029-53.

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

Longhi, Simonetta, Peter Nijkamp, and Jacques Poot. 2005. A Meta-Analytic Assessment of the Effect of Immigration on Wages *Journal of Economic Surveys* 86, no. 3 451-477.

Manacorda Marco, Alan Manning and John Wadsworth. 2006. The Impact of Immigration on the Structure of Male Wages: Theory and Evidence from Britain IZA Discussion paper 2352. Bonn, Germany.

Murphy, Kevin and Finis Welch. 1992. The Structure of Wages. *The Quarterly Journal of Economics* 107, no. 1: pp. 285-326

National Research Council. 1997. The New Americans: Economic, Demographic, and Fiscal Effects of Immigration. National Academy Press, Washington D.C..

Ottaviano, Gianmarco, and Giovanni Peri. 2005. Cities and Cultures. *Journal of Urban Economics* 58, no.2: 304-307.

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

Ottaviano, Gianmarco, and Giovanni Peri. 2006b. The Economic Value of Cultural Diversity: Evidence from U.S. Cities. *Journal of Economic Geography* 6, no1: 9-44.

Ottaviano, Gianmarco, and Giovanni Peri. 2007. The Effect of Immigration on U.S. Wages and Rents: A General Equilibrium Approach. CReAM Discussion Paper no 13/07 London, UK.

Peri, Giovanni, and Chad Sparber, 2008. Task Specialization, Immigration and Wages. CReAM Discussion Paper 02/08, March 2008.

Ramsey, Frank. 1928. A Mathematical Theory of Saving. *Economic Journal* 38, no.152: 543-559.

Raphael S. and E. Smolensky. 2008. Immigration and Poverty in the Unites States. Manuscript, UC Berkeley, April 2008.

Romer, David. 2006. Advanced Macroeconomics. McGraw-Hill, Third Edition. New York, NY.

King, Miriam, Steven Ruggles, Trent Alexander, Donna Leicach, and Matthew Sobek. 2008. Integrated Public Use Microdata Series, Current Population Survey: Version 2.0. [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor].

Solow, Robert. 1956. A Contribution to the Theory of Economic Growth. *Quarterly Journal of Economics* 70 no. 1: 65-94.

Welch, Finis. 1979. Effects of Cohort Size on Earnings: The Baby Boom Babies Financial Boost. *Journal of Political Economy* 87, no. 5: 65-97.

A Theoretical Appendix: Wage Reaction to Immigration

We denote the change in the supply of foreign-born due to immigration between two censuses in group k, j as $\Delta F_{kjt} = F_{kjt+10} - F_{kjt}$. We can use the demand functions (10) and (11) to derive the effect of immigration on native and foreign-born wages. The resulting expressions are as follows:

$$\left(\frac{\Delta w_{Dbkjt}}{w_{Dbkjt}}\right)^{Total} = \frac{1}{\sigma_{HL}} \sum_{c\in B}\sum_{q\in E}\sum_{i=1}^{8}\left(s_{Fcqit}\frac{\Delta F_{cqit}}{F_{cqit}}\right) + \left(\frac{1}{\sigma_{bb}} - \frac{1}{\sigma_{HL}}\right)\left(\frac{1}{s_{bt}}\right)\sum_{q\in b}\sum_{i=1}^{8}\left(s_{Fbqit}\frac{\Delta F_{bqit}}{F_{bqit}}\right) + \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{bb}}\right)\left(\frac{1}{s_{bkt}}\right)\sum_{i=1}^{8}\left(s_{Fbkit}\frac{\Delta F_{bkit}}{F_{bkit}}\right) + \left(\frac{1}{\sigma_{immi}} - \frac{1}{\sigma_{EXP}}\right)\left(\frac{1}{s_{bkjt}}\right)\left(s_{Fbkjt}\frac{\Delta F_{bkjt}}{F_{bkjt}}\right) + (1-\alpha)\left(\frac{\Delta\kappa_t}{\kappa_t}\right)_{immigration} \tag{25}$$

and:

$$\left(\frac{\Delta w_{Fbkjt}}{w_{Fbkjt}}\right)^{Total} = \frac{1}{\sigma_{HL}} \sum_{c\in B}\sum_{q\in E}\sum_{i=1}^{8}\left(s_{Fcqit}\frac{\Delta F_{cqit}}{F_{cqit}}\right) + \left(\frac{1}{\sigma_{bb}} - \frac{1}{\sigma_{HL}}\right)\left(\frac{1}{s_{bt}}\right)\sum_{q\in b}\sum_{i=1}^{8}\left(s_{Fbqit}\frac{\Delta F_{bqit}}{F_{bqit}}\right) + \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{bb}}\right)\left(\frac{1}{s_{bkt}}\right)\sum_{i=1}^{8}\left(s_{Fbkit}\frac{\Delta F_{bkit}}{F_{bkit}}\right) + \left(\frac{1}{\sigma_{immi}} - \frac{1}{\sigma_{EXP}}\right)\left(\frac{1}{s_{bkjt}}\right)\left(s_{Fbkjt}\frac{\Delta F_{bkjt}}{F_{bkjt}}\right) + (1-\alpha)\left(\frac{\Delta\kappa_t}{\kappa_t}\right)_{immigration} - \frac{1}{\sigma_{immi}}\frac{\Delta F_{bkjt}}{F_{bkjt}} \tag{26}$$

where s_{Fbkjt} is the share of overall wages paid in year t to foreign workers in education group b, subgroup k, with experience j[28]. Analogously, s_{bkjt} is the share of the total wage bill in year t accounted for by all workers in education group b, subgroup k and with experience j.[29]

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 U.S.- and foreign-born workers, is given by the following expression: $\overline{w}_t = \sum_b \sum_k \sum_j (w_{Fbkjt}\varkappa_{Fbkjt} + w_{Dbkjt}\varkappa_{Dbkjt})$ where we indicate with $\varkappa_{Fbkjt}$ ($\varkappa_{Dbkjt}$) the hours worked by immigrants (natives) of education b, subgroup k and experience j as a share of total hours worked in the economy. Similarly, the average wage of U.S.-born and foreign-born workers can be expressed as weighted averages of individual group wages: $\overline{w}_{Dt} = \sum_b \sum_k \sum_j (w_{Dbkjt}\varkappa_{Dbkjt})/\sum_b \sum_k \sum_j \varkappa_{Dbkjt}$ and $\overline{w}_{Ft} = \sum_b \sum_k \sum_j (w_{Fbkjt}\varkappa_{Fbkjt})/\sum_b \sum_k \sum_j \varkappa_{Fbkjt}$, respec-

[28] $s_{Fbkjt} = \dfrac{w_{Fbkjt}F_{bkjt}}{\sum_{c\in B}\sum_{q\in K}\sum_{i=1}^{8}(w_{Fcqit}F_{cqit} + w_{Dcqit}D_{cqit})}$

[29] $s_{bkjt} = \dfrac{w_{Fbkjt}F_{bkjt} + w_{Dbkjt}D_{bkjt}}{\sum_{c\in B}\sum_{q\in K}\sum_{i=1}^{8}(w_{Fcqit}F_{cqit} + w_{Dcqit}D_{cqit})}$

tively. The percentage change in the average wage of native workers as a consequence of changes in each group's wage due to immigration is given by the following expressions:

$$\frac{\Delta \overline{w}_{Dt}}{\overline{w}_{Dt}} = \frac{\sum_b \sum_k \sum_j (\frac{\Delta w_{Dbkjt}}{w_{Dbkjt}} \frac{w_{Dbkjt}}{\overline{w}_{Dt}} \varkappa_{Dbkjt})}{\sum_b \sum_k \sum_j \varkappa_{Dkjt}} = \frac{\sum_b \sum_k \sum_j (\frac{\Delta w_{Dbkjt}}{w_{Dbkjt}}) s_{Dbkjt}}{\sum_b \sum_k \sum_j s_{Dbkjt}} \tag{27}$$

where $\frac{\Delta w_{Hbkjt}}{w_{Hbkjt}}$ represents the percentage change in the wage of U.S.-born in group b, k, j due to immigration, and its expression is given in (25). Similarly, the percentage change in the average wage of foreign-born workers is:

$$\frac{\Delta \overline{w}_{Ft}}{\overline{w}_{Ft}} = \frac{\sum_b \sum_k \sum_j (\frac{\Delta w_{Fbkjt}}{w_{Fbkjt}} \frac{w_{Fbkjt}}{\overline{w}_{Ft}} \varkappa_{Fkjt})}{\sum_b \sum_k \sum_j \varkappa_{Fbkjt}} = \frac{\sum_b \sum_k \sum_j (\frac{\Delta w_{Fbkjt}}{w_{Fbkjt}}) s_{Fbkjt}}{\sum_b \sum_k \sum_j s_{Fbkjt}} \tag{28}$$

where $\frac{\Delta w_{Fbkjt}}{w_{Fbkjt}}$ represents the percentage change in the wage of foreign-born in group b, k, j due to immigration, and its expression is given in (26). 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:

$$\frac{\Delta \overline{w}_t}{\overline{w}_t} = \sum_b \sum_k \sum_j \left(\frac{\Delta w_{Fbkjt}}{w_{Fbkjt}} \frac{w_{Fbkjt}}{\overline{w}_{Ft}} \varkappa_{Fbkjt} + \frac{\Delta w_{Dbkjt}}{w_{Dbkjt}} \frac{w_{Dkjt}}{\overline{w}_{Dt}} \varkappa_{Dbkjt} \right) = \sum_b \sum_k \sum_j \left(\frac{\Delta w_{Fbkjt}}{w_{Fbkjt}} s_{Fbkjt} + \frac{\Delta w_{Dbkjt}}{w_{Dbkjt}} s_{Dbkjt} \right) \tag{29}$$

Recall that the variables s_{Fbkjt} and s_{Dbkjt} represent the group's share in total wages and notice that the correct weighting in order to obtain the percentage change on *average wages* is the share in the wage bill and not the share in employment. Due to constant returns to scale of the aggregate production function (1), while some of the wage changes are positive and others negative, when weighted by their wage shares the summation of these changes equals 0 once capital has adjusted fully (i.e., in the long run); hence, the change in the overall average wage in (29) is approximately 0 in the long run. However, if U.S.- and foreign-born workers are not perfectly substitutable, the overall effect on the wage of U.S.-born workers (27) need not be 0 but will be positive instead and the effect on the average wage of foreign-born workers (28) will be negative. We also adopt the same averaging procedure (weighting percentage changes by wage shares) in calculating the effect of immigration on specific groups of U.S.-born and foreign-born workers. For instance, the changes in average wages of college educated, U.S.-born workers is calculated as $\sum_j \left(\frac{\Delta w_{DCOGjt}}{w_{DCOGjt}} s_{DCOGjt} \right) / \sum_j s_{DCOGjt}$ and the change in average wages of foreign-born with no high school diploma is calculated as $\sum_j \left(\frac{\Delta w_{F,SHSjt}}{w_{F,SHSjt}} s_{F,SHSjt} \right) / \sum_j s_{F,SHS,jt}$, and so on.

B Data Appendix for the IPUMS Census Data

We downloaded the IPUMS data on June 1st, 2008. The data are relative to 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 it 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.1 Definition of the Samples and Restrictions

B.1.1 EMPLOYMENT SAMPLE

For the EMPLOYMENT SAMPLE our definition aims at including all workers who supplied some hours of work and who were in the 32 cells (defined by education and experience) that we consider. The relevant eliminations made in the sample were:

1) Eliminate people living in group quarters (military or convicts), which are those with the gq variable equal to 0, 3 or 4.

2) Eliminate people younger than 18.

3) Eliminate those who worked 0 weeks last year, which corresponds to wkswork2=0 in 1960 and 1970 and wkswork1=0 in 1980-1990-2000 and ACS.

4) Once we calculate experience as age-(time first worked), where (time first worked) is 17 for workers with no HS degree, 19 for HS graduates, 21 for workers with some college education and 23 for college graduates, we eliminate all those with experience <1 and >40.

Construction of hours worked and employment by cell

To calculate the total amount of hours worked by natives and immigrants, male and female, in each education-experience cell, we add the hours worked by each person multiplied by her personal weight (PERWT) in the cell.

To calculate the total employment (body-count) for natives and immigrants, male and female, in each cell we sum the personal weight (PERWT) of each individual in the cell.

B.1.2 WAGE SAMPLE

For the WAGE SAMPLE we identify only employee workers. Since we weight the weekly wage of each worker for the hours of work supplied when we calculate the average weekly wage within a group, the heterogeneity in attachment to the labor force is accounted for.

For the WAGE SAMPLE used in Tables 2, 4 and 5:

a) Apply the same elimination as for the Employment sample

b) Eliminate those workers who do not report valid salary income (999999) or report 0.

c) Eliminate the self-employed (keeping those for whom the variable CLASSWKD is between 20 and 28).

For the WAGE SAMPLE used in Table 3:

a) Apply all elimination as in the above wage sample

b) Eliminate those who are still enrolled in school (variable SCHOOL = 2) or, for year 1970, we construct

gen school=higraded - (int(higraded/10))*10

and also eliminate SCHOOL==2

Construction of the average weekly wage for each group

In each education-experience cell we average the weekly wage of individuals, each weighted by the hours worked by the individual. Hence individuals with few hours worked (low job attachment) are correspondingly weighted little in the calculation of the average wage of the group.

B.2 Individual Variables Definition and Description

Education: We defined education groups as: Some High School (SHS), High School Graduate (HSG), Some College (SCO) and College Graduates (COG). All groups in each year are defined using the variable EDUCREC which was built in order to consistently reflect the variables HIGRADE and EDUC99. In particular, we define as SHS those with EDUCREC<=6, HSG are those with EDUCREC=7, SCO are those with EDUCREC=8 and COG are those with EDUCREC=9.

Experience: Defined as potential experience, assigns to each schooling group a certain age reflecting the beginning of their working life; in particular, the initial working ages are: 17 years for SHS, 19 years for HSG, 21 years for SCO and 23 years for COG.

Immigration Status: In each year, only people who are not citizens or who were naturalized citizens are counted as immigrants. This is done using the variable CITIZEN and by attributing the status of foreign-born to people when the variable is equal to 2 or 3. In 1960, the variable is not available and the selection is done using the variable BPLD (birthplace, detailed) and attributing the status of foreign-born to all of those for which BPLD>15000, except for the codes 90011 and 90021 which indicate U.S. citizens born abroad.

Weeks Worked in a Year: For the censuses 1960 and 1970 the variable used to define weeks worked in the last year is WKSWORK2, which defines weeks worked in intervals. We choose the median value for each interval so that we impute to individuals weeks worked in the previous year according to the following criteria: 6.5 weeks if wkswork2=1; 20 weeks if wkswork2=2; 33 weeks if wkswork2=3; 43.5 weeks if wkswork2=4; 48.5 weeks if wkswork2=5; 51 weeks if wkswork2==6. For the censuses 1980, 1990, 2000 and ACS we use the variable wkswork1 which records the exact number of weeks worked last year.

Hours Worked in a Week: For census years 1960 and 1970 the variable used is HRSWORK2 which measures the hours worked during the last week, using intervals. We attribute to each interval its median value and measure the number of hours per week worked by an individual according to the following criteria: 7.5 hours if hrswork2=1; 22 hours if hrswork2=2; 32 hours if hrswork2=3; 37 hours if hrswork2=4; 40 hours if hrswork2=5; 44.5 hours if hrswork2=6; 54 hours if hrswork2=7; 70 hours if hrswork2==8. For the censuses 1980, 1990, 2000 and ACS we use the variable UHRSWORK which records the exact number of hours worked in the usual week by a person.

Hours Worked in a Year: This is the measure of labor supply by an individual and it is obtained multiplying Hours Worked in a Week by Weeks Worked in a Year, as defined above.

Yearly Wages: The yearly wage in constant 1999 US $ is calculated as the variable INCWAGE multiplied by the price deflator suggested in the IPUMS, which is the one below. Recall that each census and ACS is relative to the previous year so the deflators below are those to be applied to years 1960, 1970, 1980, and so on:

$Year$	1959	1969	1979	1989	1999	2005
$Deflator$	5.725	4.540	2.314	1.344	1.000	0.853

Topcodes for Yearly Wages: Following an established procedure we multiply the topcodes for yearly wages in 1960, 1970 and 1980 by 1.5.

Weekly Wages: The weekly wage for an individual is constructed by dividing the yearly wage as defined above by the number of weeks worked in a year, as defined above.

C Data Appendix for the IPUMS-CPS data

We downloaded the IPUMS-CPS data on April 28th 2008 including the years 1963-2006 in the extraction.

Just as for the Census, we constructed an *employment sample* and a *wage sample.* We used the first to calculate measures of hours worked and employment and the second 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 construct hours worked, employment and average wage for each of 4 education groups (workers with no high school, high school graduates, workers with some college and college graduates) following as closely as possible the procedure described in Katz and Murphy (1992), page 67-68 and detailed below.

C.1 Definition of the Samples and Restrictions

C.1.1 EMPLOYMENT SAMPLE

For the EMPLOYMENT SAMPLE our definition aims at including all workers who supplied some hours of work and who were in the education by experience sample as the one used for Census data. The relevant eliminations made in the main sample where:

1) Eliminate people living in group quarters (military or convicts), which are those with the gq variable equal to 0, 3 or 4.

2) Eliminate people younger than 18.

3) Eliminate those who worked 0 weeks last year which corresponds to wkswork2=0 until 1975 and wkswork1=0 after 1975. Eliminate those who worked 0 hours by omitting hrswork=0 until 1975 and uhrswork=0 after 1975.

4) Once we calculate experience as age-(time first worked), where (time first worked) is 17 for workers with no HS degree, 19 for HS graduates, 21 for workers with some college education and 23 for college graduates, we eliminate all those with experience <1 and >40.

Construction of the hours worked and employment by education group and year

We first calculate the total amount of hours worked by sex-education-experience cell in each year by adding up the hours worked by each person in the cell, multiplied by her personal weight (PERWT). Then we calculate the average weekly wage in each of the four education groups (SHS, HSG, SCO, COG) over the 1963-2006 period and we sum up in each education group-year the hours worked by each experience-sex group scaled by the average (1963-2006) weekly wages of the group relative to males with 10-15 years of experience. This converts hours worked to equivalent hours assuming that different groups have different labor effectiveness. We use the same procedure to calculate employment in each education group per year.

C.1.2 WAGE SAMPLE

The construction of the Wage sample follows these steps:

a) Apply the same elimination as for the Employment sample

b) Eliminate those workers who do not report valid salary income (999999) or report 0.

c) Eliminate the self-employed (keep those for whom variable CLASSWKR is between 20 and 28).

Construction of the average weekly wage by education cell in each year.

In each of the sex-education-experience cells in each year we average the weekly wage of individuals, each weighted by the hours worked by the individual. Then we aggregate the average wage of each cell within the four education groups for each year by weighting the average weekly wage in the sex-education-experience cells by the average (1963-2006) hours worked by the education-experience-sex group relative to the total of the education group. This keeps the composition constant within the education group when calculating average wages.

C.2 Individual Variables Definition and Construction

Education: We defined four education groups: Some High School (SHS), High School Graduates (HSG), Some College (SCO) and College Graduates (COG). All groups in each year are defined using the variable EDUCREC which was built in order to consistently reflect the variables HIGRADE and EDUC99. In particular, we define as SHS those with EDUCREC<=6, then HSG are those with EDUCREC=7, SCO are those with EDUCREC=8 and COG are those with EDUCREC=9.

Experience: Defined as potential experience, assigning to each schooling group a certain age reflecting the start of their working life; in particular, the initial working ages are: 16 years for SHS, 19 years for HSG, 21 years for SCO and 23 years for COG.

Weeks Worked in a Year: For the CPS up to1975 the variable used to define weeks worked in the last year is WKSWORK2, which defines weeks worked in intervals. We choose the median value for each interval so that we impute to individuals weeks worked in the previous year according to the following criteria:

6.5 weeks if wkswork2=1; 20 weeks if wkswork2=2; 33 weeks if wkswork2=3; 43.5 weeks if wkswork2=4; 48.5 weeks if wkswork2=5; 51 weeks if wkswork2==6.

For the CPS after 1975 we use the variable wkswork1 which records the exact number of weeks worked last year.

Hours Worked in a Week: For the CPS up to 1975 we use hrswork, which records the number of hours worked last week, and after 1975 we use uhrswork which records the exact number of hours worked in a usual week by a person.

Hours Worked in a Year: This is the measure of labor supply by an individual and it is obtained multiplying Hours Worked in a Week by Weeks Worked in a Year, as defined above.

Yearly Wages: The yearly wage in current US $ is calculated as the variable INCWAGE

Weekly Wages: The weekly wage for an individual is constructed by dividing the yearly wage as defined above by the number of weeks worked in a year, as defined above.

Hispanic: The Hispanic ethnicity indicator, used to proxy immigrants after 1970, is obtained from the variable HISPAN.

Tables

Table 1:
Immigration and Native Wages, 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	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	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%**
High School Degree or Less	**All Experience groups**	**13.2%**	**-1.5%**
Some College Education	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	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%**
Some College and More	**All Experience groups**	**10.0%**	**4.5%**

Table 2

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

Wage Sample: All people who worked for wages except the self-employed, weighted by hours worked

Specification	**(1) No Fixed Effects**	**(2) Basic**	**(3) Add Time Effects**	**(4) Add Time by Experience effects**	**(5) Add Time by Education effects**	**(6) BGH (2008) Table 4 Column (3)**	**Number of Observations**
Sample:							
Men	-0.048*** (0.008)	-0.063*** (0.009)	-0.028** (0.013)	-0.068*** (0.012)	0.009 (0.027)	0.009 (0.034)	192
Women	-0.043*** (0.008)	-0.057*** (0.012)	-0.073*** (0.017)	-0.095*** (0.010)	-0.058* (0.030)	-0.044** (0.022)	192
Pooled Men and Women	-0.032*** (0.009)	-0.042*** (0.010)	-0.024* (0.015)	-0.066*** (0.010)	-0.015 (0.035)	-0.011 (0.031)	192
IV (using relative employment) Pooled M-W	-0.035*** (0.007)	-0.043** (0.010)	-0.027* (0.014)	-0.066*** (0.010)	-0.038 (0.039)	-0.024 (0.032)	192
1970-2006 Pooled M-W	-0.032*** (0.009)	-0.042*** (0.010)	-0.039** (0.016)	-0.062*** (0.012)	-0.036 (0.039)	n.a	160
Less Educated Workers Only Pooled M-W	-0.040*** (0.009)	-0.052*** (0.010)	-0.015 (0.026)	-0.032*** (0.010)	-0.072* (0.037)	n.a	96
Young workers Only Pooled M-W	-0.016 (0.011)	-0.022** (0.012)	-0.063*** (0.023)	-0.071*** (0.017)	-0.041 (0.049)	n.a	96
Included fixed effects:							
Education by Experience effects (32 in total)	No	Yes	Yes	Yes	Yes	Yes	
Year Effects (6 in total)	No	No	Yes	Yes	Yes	Yes	
Year by Experience Effects (48 in total)	No	No	No	Yes	Yes	Yes	
Year by Education Fixed effects (24 in total)	No	No	No	No	Yes	Yes	

Note: Each cell reports the estimate of the parameter $\mathbf{-1/\sigma_{IMMI}}$. The estimated specification in column (2) is exactly as in equation (14) in the main text. The other specifications omit or include other dummies. Column (6) reports the estimates from Borjas, Grogger and Hanson (2008) where available. Each observation in a regression represents one of 32 education-experience cells over a considered year (1960, 1970, 1980, 1990, 2000 and 2006). The dependent variable is the logarithm of the relative foreign-native average wage in the cell. The average wage for each group in the cell is the hours-weighted average weekly wage including individuals working at least one week, not self-employed and earning positive salary. The explanatory variable is the logarithm of the relative foreign-native labor supplied by individuals in the cell measured as hours worked by individuals not in group quarters. In the fourth row we instrument relative hours worked with relative employment. Each observation is weighted in the regression by the number of observations (employment) in the cell. In parenthesis we report the heteroskedasticity-robust standard errors, clustered over the 32 education-experience groups. ***= significant at 1% level; **=significant at 5% level; *= significant at 10% level.

Table 3

Estimates of (-1/σ_{IMMI}), National Census and ACS, U.S. data 1960-2006

Wage Sample: all people who worked for wages- except for the self-employed and people enrolled in school- weighted by hours worked

Specification	**(1) No Fixed Effects**	**(2) Basic**	**(3) Add Time Effects**	**(4) Add Time by Experience effects**	**(5) Add Time by Education effects**	**(6) BGH (2008) Table 4 Column (1)**	**Number of Observations**
Sample:							
Men	-0.053*** (0.006)	-0.068*** (0.008)	-0.037*** (0.010)	-0.077*** (0.013)	0.036 (0.024)	0.044 (0.029)	192
Women	-0.047*** (0.007)	-0.059*** (0.011)	-0.074*** (0.015)	-0.094*** (0.011)	-0.01 (0.023)	-0.025 (0.017)	192
Pooled Men and Women	-0.037*** (0.006)	-0.047*** (0.008)	-0.031*** (0.012)	-0.074*** (0.010)	0.010 (0.020)	0.011 (0.025)	192
IV (using relative employment) Pooled M-W	-0.039*** (0.006)	-0.048*** (0.008)	-0.034*** (0.012)	-0.073*** (0.012)	0.002 (0.021)	0.002 (0.025)	192
1970-2006 Pooled M-W	-0.038*** (0.006)	-0.046*** (0.009)	-0.046*** (0.012)	-0.068*** (0.012)	-0.008 (0.029)	n.a	160
Less Educated Workers Only Pooled M-W	-0.046*** (0.005)	-0.057*** (0.007)	0.007 (0.011)	-0.037*** (0.009)	-0.019 (0.018)	n.a	96
Young workers Only Pooled M-W	-0.024*** (0.008)	-0.028** (0.010)	-0.078*** (0.017)	-0.086*** (0.017)	0.026 (0.029)	n.a	96
Included fixed effects:							
Education by Experience effects (32 in total)	No	Yes	Yes	Yes	Yes	Yes	
Year Effects (6 in total)	No	No	Yes	Yes	Yes	Yes	
Year by Experience Effects (48 in total)	No	No	No	Yes	Yes	Yes	
Year by Education Fixed effects (24 in total)	No	No	No	No	Yes	Yes	

Note: Each cell reports the estimate of the parameter **-1/σ_{IMMI}**. The estimated specification in column (2) is exactly as in equation (14) in the main text. The other specifications omit or include other dummies. Column (6) reports the corresponding estimates from Borjas, Grogger and Hanson (2008) where available. Each observation in a regression represents one of 32 education-experience cells over a considered year (1960, 1970, 1980, 1990, 2000 and 2006). The dependent variable is the logarithm of the relative foreign-native average wage. The average wage for each group in the cell is the hour-weighted average weekly wage including individuals working at least one week, not self-employed, not attending school and earning positive salary. The explanatory variable is the logarithm of the relative foreign-native labor supplied by individuals in the cell, measured as hours worked. In the fourth row we instrument relative hours worked with relative employment. Each observation is weighted by the number of observations (employment) in the cell. In parenthesis we include the heteroskedasticity-robust standard errors, clustered over the 32 education-experience groups. ***= significant at 1% level; **=significant at 5% level; *= significant at 10% level.

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

	(1) Basic Specification (use σ_{IMMI}=20 to construct N_{kjt})	(2) Basic Specification (assuming $\sigma_{IMMI}=\infty$)	(3) Add Time by Experience fixed effects	Number of Observations
Sample:				
Men	-0.16*** (0.05)	-0.16*** (0.06)	-0.05 (0.04)	192
Women	-0.05 (0.05)	-0.05 (0.05)	-0.03 (0.04)	192
Pooled Men and Women	-0.14*** (0.04)	-0.14** (0.04)	-0.02 (0.03)	192
Pooled Men and Women Employment as Measure of Labor Supply	-0.13*** (0.05)	-0.13** (0.05)	-0.03 (0.03)	192
Pooled Men and Women 1970-2006	-0.07*** (0.03)	-0.07*** (0.03)	-0.01 (0.03)	160
	Included fixed effects:			
Education by Experience Effects (32 in total)	Yes	Yes	Yes	
Year by Education Fixed Effects (24 in total)	Yes	Yes	Yes	
Year by Experience Effects (48 in total)	No	No	Yes	

Note: Each cell reports the estimate of the parameter **$-1/\sigma_{EXP}$**. Each observation represents one of 32 education-experience cells over one of the considered years (1960, 1970, 1980, 1990, 2000 and 2006). The dependent variable is the logarithm of the average weekly wage of native and immigrant workers in the cell (Men, Women or Pooled M-W depending on the row) constructed as the hours-weighted average weekly wage including all individuals working at least one week, not self-employed and earning positive salary. The explanatory variable is the logarithm of the labor composite N_{kjt} whose construction is described in the text. In constructing N_{kjt} we use hours worked as a measure of individual labor supply (except in the fourth row where we use employment). The method of estimation is 2SLS using the logarithm of labor supplied by foreign-born workers (in hours or in employment) in the cell $\ln(F_{kjt})$ as an instrument for total labor supply $\ln(N_{kjt})$ in the cell. Each observation is weighted by the cell employment. The Basic specification is as equation 917) in the text. In parenthesis we include the heteroskedasticity-robust standard errors, clustered over the 32 education-experience groups.
***= significant at 1% level; **=significant at 5% level; *= significant at 10% level.

Table 5
Estimates of ($-1/\sigma_{EDU}$), National Census and ACS, U.S. data 1960-2006

	(1) Basic Specification (assuming σ_{EXP}=6.6; σ_{IMMI}=20)	(2) Basic Specification (assuming $\sigma_{EXP}=\infty$; $\sigma_{IMMI}=\infty$)	(3) With Common Year Effects and Education-Specific Trends	(4) With Education-Main Effects and Education-Specific Trends	Number of Observations
Men	-0.44*** (0.19)	-0.42** (0.18)	-0.29*** (0.10)	-0.65 (0.86)	24
Women	-0.46*** (0.20)	-0.43*** (0.19)	-0.35** (0.15)	-0.48 (0.62)	24
Pooled Men and Women	-0.43*** (0.17)	-0.41*** (0.16)	-0.30*** (0.12)	-0.63 (0.74)	24
Pooled Men and Women Employment as a Measure of Labor Supply	-0.40*** (0.13)	-0.38*** (0.12)	-0.29*** (0.10)	-0.70 (0.90)	24
Pooled Men and Women 1970-2006	-0.24*** (0.11)	-0.23*** (0.11)	-0.25* (0.13)	-0.17* (0.09)	20
Included fixed effects					
Education-Specific Time Trend	Yes	Yes	Yes	Yes	
Common Year -Fixed Effects	No	No	Yes	No	
Education-Specific Fixed Effect	No	No	No	Yes	

Note: Each cell reports the estimate of the parameter **$-1/\sigma_{EDU}$**. Each observation represents one of four education cells in each of the considered years (1960, 1970, 1980, 1990, 2000 and 2006). The dependent variable is the logarithm of the average weekly wage of native and immigrant workers in the cell (Men, Women or Pooled M-W depending on the row) constructed as an hour-weighted average weekly wage including all individuals working at least one week, not self-employed and earning positive salary. The explanatory variable is the logarithm of the labor composite N_{kt} whose construction is described in the text. In constructing N_{kj} we use hours worked as a measure of individual labor supply (except in the fourth row where we use employment). The method of estimation is 2SLS using the logarithm of labor supplied by foreign-born workers (in hours or in employment) in the cell, $\ln(F_{kt})$ as an instrument for total labor supply $\ln(N_{kt})$in the cell. Each observation is weighted by the cell employment. The basic specification is as specified in equation (20) in the text. In parenthesis we include the heteroskedasticity-robust standard errors, clustered over the four education groups.
***= significant at 1% level; **=significant at 5% level; *= significant at 10% level.

Table 6
Estimates of ($-1/\sigma_{HL}$), ($-1/\sigma_{HH}$), and ($-1/\sigma_{LL}$) CPS, U.S. data 1963-2006,
Katz and Murphy (1992) method

<table>
<tr><th></th><th>(1)
Estimates of
$-1/\sigma_{HL}$</th><th>(2)
Estimates of
$-1/\sigma_{LL}$</th><th>(3)
Estimates of
$-1/\sigma_{HH}$</th><th>Number of Observations</th></tr>
<tr><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Pooled Men and Women
With "Some College" split between H and L</td><td>-0.54***
(0.06)
[0.07]</td><td rowspan="2">-0.029
(0.018)
[0.021]</td><td rowspan="2">-0.16*
(0.08)
[0.10]</td><td>44</td></tr>
<tr><td>Pooled Men and Women
With "Some College" in H</td><td>-0.32***
(0.06)
[0.08]</td><td>44</td></tr>
<tr><td>Pooled Men and Women
Employment as a Measure of Labor Supply</td><td>-0.66***
(0.07)
[0.09]</td><td>-0.039
(0.020)
[0.024]</td><td>-0.08
(0.09)
[0.11]</td><td>44</td></tr>
<tr><td>Pooled Men and Women
1970-2006</td><td>-0.52***
(0.06)
[0.08]</td><td>0.021
(0.028)
[0.025]</td><td>-0.13
(0.08)
[0.09]</td><td>36</td></tr>
</table>

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 and identical to Katz and Murphy (1992). 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 7
Simulated Wage Effects of Immigrants, 1990-2006:
Long Run Effects

	Parameters From the Existing Labor Literature			**Parameters from Existing Labor Literature and σ_{IMMI} from Our Estimates**			**Parameters from Our Estimates**			**Borjas and Katz (2007) Parameters**
	(1) Low	(2) High	**(3) Typical**	(4) Low	(5) High	**(6) Typical**	(7) Low	(8) High	**(9) Typical**	**(10)**
σ_{HL}	1.4	2	**1.5**	1.4	2	**1.5**	1.4	2	**2**	**2.4**
σ_{HH}	∞	∞	∞	∞	∞	∞	10	10	**10**	**2.4**
σ_{LL}	∞	∞	∞	∞	∞	∞	10	50	**20**	**2.4**
σ_{EXP}	3.3	10	**5**	3.3	10	**5**	6.2	7.7	**7**	**3**
σ_{IMMI}	∞	∞	∞	15	30	**20**	20	20	**20**	∞
% Real Wage Change of US-Born Workers Due to Immigration, 1990-2006										
Less than HS	-0.6%	-0.5%	**-0.5%**	+1.0%	+0.5%	**+0.7%**	-0.3	+0.6	**+0.3**	**-4.7%**
HS graduates	-0.3%	-0.2%	**-0.3%**	+0.3%	+0.1%	**+0.2%**	+0.4	+0.3	**+0.4**	**+0.9%**
Some CO	+0.1%	+0.1%	**+0.1%**	+0.6%	+0.3%	**+0.5%**	+1.0	+0.1	**+0.9**	**+2.2%**
CO graduates	+0.1%	+0.1%	**+0.1%**	+1.1%	+0.6%	**+0.9%**	+0.5	+0.5	**+0.5%**	**-1.7%**
Average US-born	0.0%	0.0%	**0.0%**	+0.8%	+0.4%	**+0.6**	+0.6%	+0.6	**+0.6%**	**+0.1%**
% Real Wage Change of Foreign-Born Workers Due to Immigration, 1990-2006										
Less than HS	-0.6%	-0.5%	**-0.5%**	-6.1%	-3.0%	**-4.6%**	-5.6%	-4.7%	**-4.9%**	**-4.7%**
HS graduates	-0.3%	-0.2%	**-0.3%**	-9.8%	-5.1%	**-7.4%**	-7.2%	-7.3%	**-7.0%**	**+0.9%**
Some CO	+0.1%	+0.1%	**+0.1%**	-6.1%	-3.1%	**-4.5%**	-4.0%	-4.1%	**-4.0%**	**+2.2%**
CO graduates	+0.1%	+0.1%	**+0.1%**	-9.2%	-5.0%	**-7.6%**	-8.0%	-8.0%	**-8.1%**	**-1.7%**
Average Foreign-born	+0.0%	0.0%	**0.0%**	-8.6%	-4.3%	**-6.4%**	-6.6%	-6.5%	**-6.4%**	**-0.8%**
Overall average	0.0%	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 in the text) weighted by its 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.

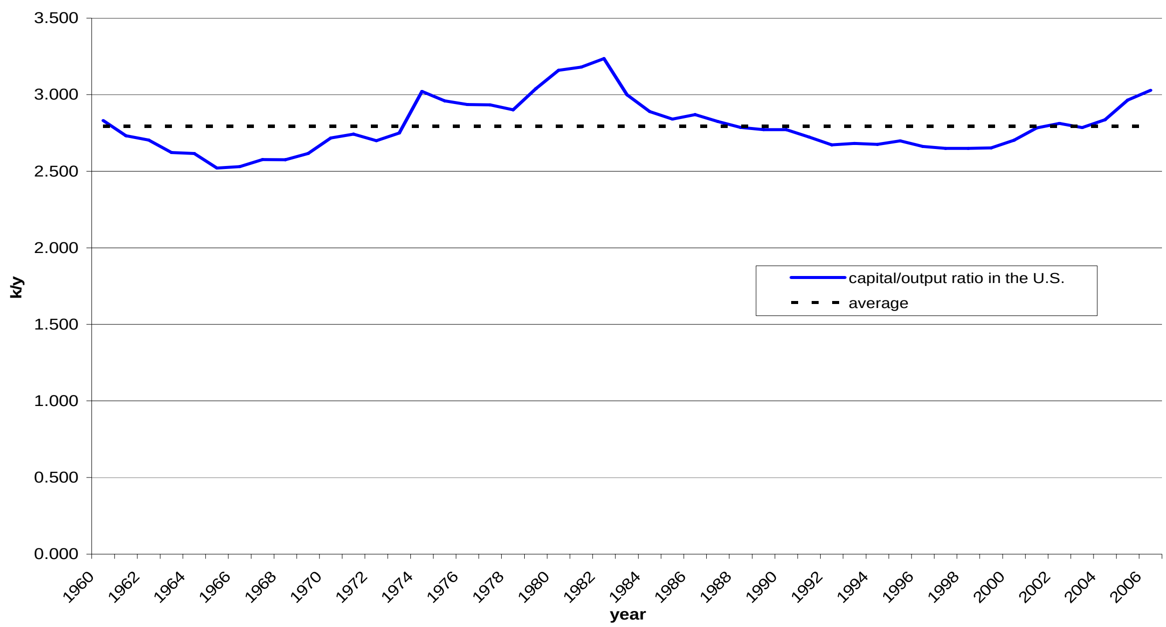
Table 8
Simulated Wage Effects of Immigrants, 1990-2006:
Short Run Effects

	1 As of 2007 (short run)	2 As of 2012 (medium run)	3 Long Run	4 Fixed K (Traditional Short Run)	5 Short Run in Borjas and Katz (2007) and Borjas (2003)
% Real Wage Change of US-Born Workers Due to Immigration, 1990-2006					
Less than HS	-0.7%	-0.3%	0.3%	-2.8%	-7.8%
HS graduates	-0.6%	-0.2%	0.4%	-2.7%	-2.2%
Some CO	0.0%	0.4%	0.9%	-2.1%	-0.9%
CO graduates	-0.5%	-0.1%	0.5%	-2.6%	-4.7%
Average, US-Born	-0.4%	0.0%	0.6%	-2.5%	-3.0%
% Real Wage Change of Foreign-Born Workers Due to Immigration, 1990-2006					
Less than HS	-6.0%	-5.6%	-4.9%	-8.1%	-7.8%
HS graduates	-8.2%	-7.8%	-7.0%	-10.3%	-2.2%
Some CO	-5.1%	-4.7%	-4.0%	-7.2%	-0.9%
CO graduates	-9.0%	-8.6%	-8.1%	-11.1%	-4.7%
Average Foreign-born	-7.5%	-7.1%	-6.4%	-9.6%	-3.0%
Overall Average: Native and US-Born	**-1.1%**	**-0.6%**	**0.0%**	**-3.2%**	**-3.2%**

Note: The simulations in the first four columns use the parameter estimates of column 9 in Table 7. The last column uses the parameter estimates of Borjas and Katz (2007), reported in column 10 of Table 7. The adjustment of the capital-labor ratio relative to its long run trend is estimated yearly using the actual inflow of immigrants and the estimated speed of adjustment of physical capital (10% per year).

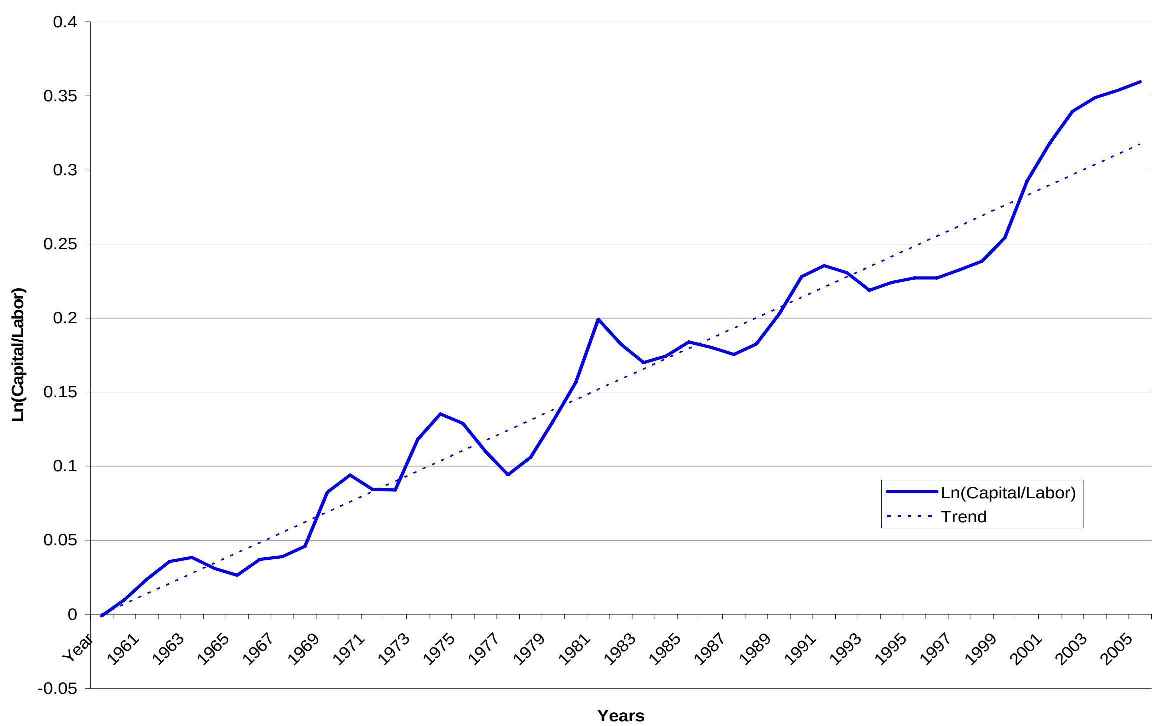
Figures

Figure 1
U.S. Capital-Output Ratio 1960-2006



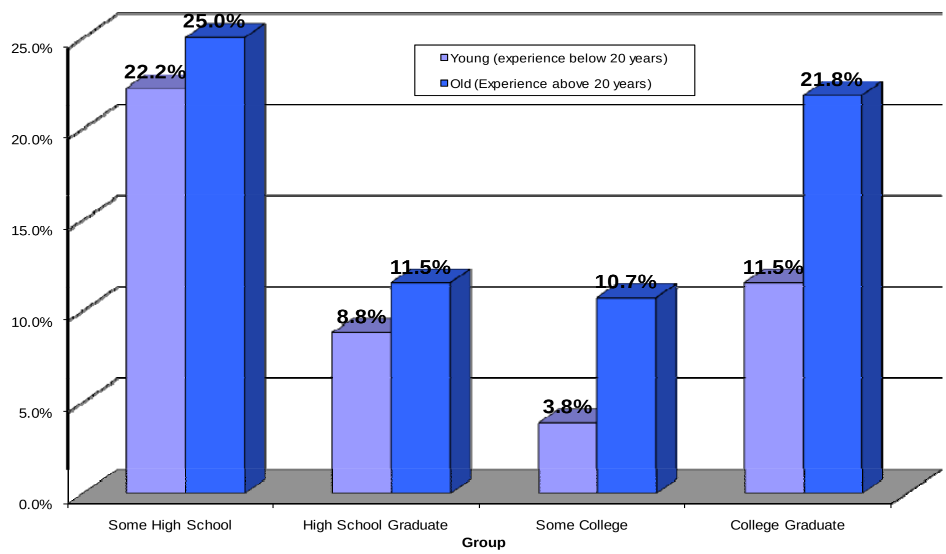
Source: Authors' calculations using BEA data on the Stock of Physical Capital and GDP

Figure 2
Log Capital-Labor Ratio and Trend 1960-2006



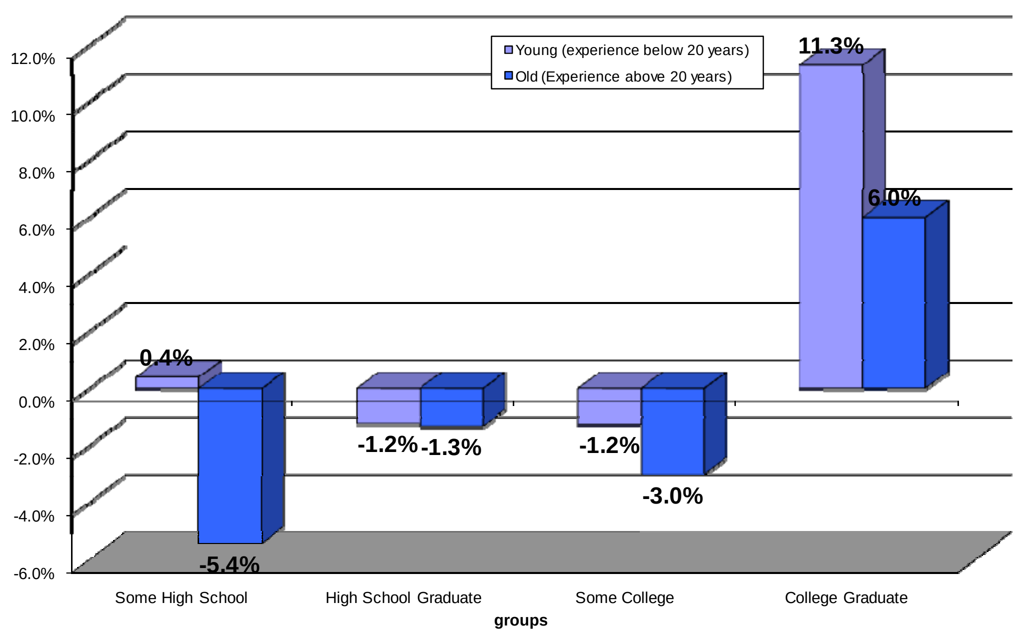
Source: Authors' calculations using BEA data on the Stock of Physical Capital and BLS data on total non-farm employment.

Figure 3
Immigration and the increase in total hours worked by group, 1990-2006



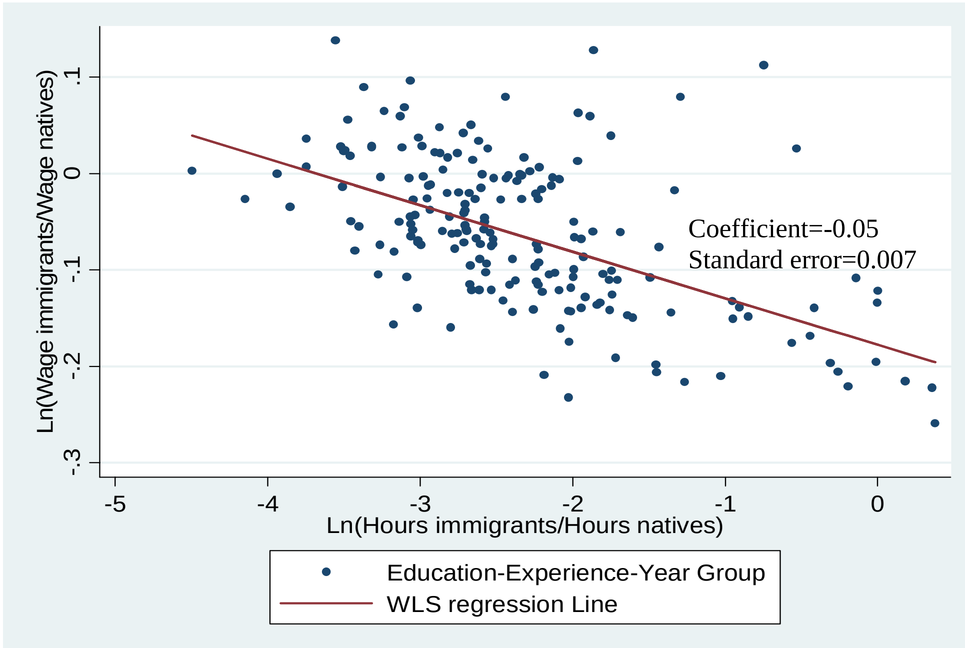
Note: Percentage Increase in Hours Worked due to immigrants, 1990-2006, by education and experience group.

Figure 4
Change in real weekly wages of US-born workers by group, 1990-2006



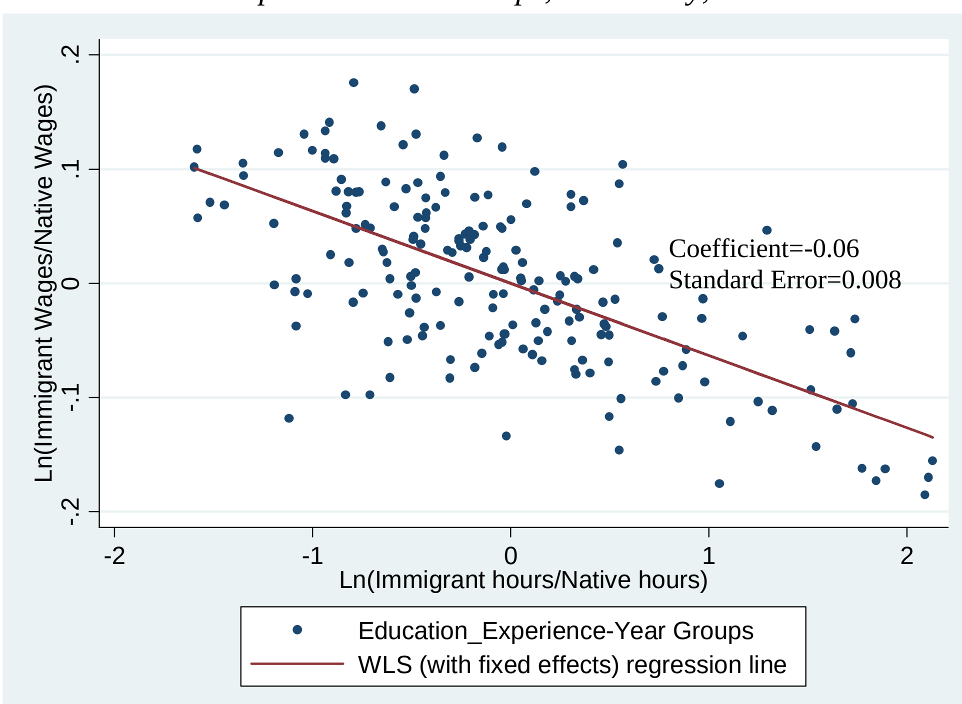
Note: Percentage changes in real weekly wages for U.S.-born workers, 1990-2006, by education and experience group.

Figure 5
Correlation between relative Immigrant-Native wages and hours worked.
Education-Experience-Year Groups, Males only, 1960-2006



Note: Each observation corresponds to an 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/ natives and the vertical axis measure the logarithm of the relative weekly wage paid to male immigrants/ natives.

Figure 6
Partial correlation between relative Immigrant-Native wages and hours worked
Education-Experience-Year Groups, Males only, 1960-2006



Note: Each observation corresponds to an education-experience group in one of the considered years (1960, 1970, 1980, 1990, 2000, 2006) The scatter-plot reports the residuals of log relative wages and log relative hours of male immigrant/natives after we control for (32) education by experience fixed effects.

Table Appendix

Table A1:
Percentage of Total Hours Worked by Foreign-Born by Group 1960-2006
Pooled Male and Female

Group		Year					
Education	**Experience**	**1960**	**1970**	**1980**	**1990**	**2000**	**2006**
No High School Degree	1 to 5	3.4%	4.9%	8.8%	19.4%	27.3%	31.3%
	6 to 10	4.1%	5.6%	13.8%	28.6%	46.2%	46.0%
	11 to 15	3.9%	6.6%	15.6%	27.4%	47.4%	56.0%
	16 to 20	4.5%	6.9%	13.2%	28.6%	45.0%	56.1%
	21 to 25	4.5%	6.5%	12.6%	27.9%	39.7%	52.6%
	26 to 30	5.3%	5.9%	11.5%	21.0%	39.5%	46.0%
	31 to 35	8.2%	5.5%	9.1%	17.6%	36.9%	43.4%
	36 to 40	12.3%	5.9%	8.1%	15.4%	27.2%	42.6%
	All Experience Levels	**6.2%**	**6.0%**	**11.2%**	**23.2%**	**39.0%**	**47.6%**
High School Graduates	1 to 5	1.5%	2.5%	3.2%	6.7%	11.6%	13.5%
	6 to 10	1.9%	2.7%	3.8%	6.9%	14.1%	17.4%
	11 to 15	2.3%	3.2%	4.6%	6.5%	13.3%	20.6%
	16 to 20	3.3%	3.3%	4.5%	7.0%	10.9%	18.5%
	21 to 25	3.0%	3.5%	5.0%	7.4%	9.7%	14.9%
	26 to 30	4.7%	4.1%	4.8%	6.9%	9.7%	11.8%
	31 to 35	6.7%	3.5%	5.0%	7.0%	9.6%	11.7%
	36 to 40	11.2%	4.9%	5.2%	6.6%	8.3%	11.4%
	All Experience Levels	**3.5%**	**3.3%**	**4.3%**	**6.9%**	**10.9%**	**14.9%**
Some College Education	1 to 5	2.6%	3.3%	4.5%	6.4%	8.4%	8.8%
	6 to 10	3.6%	4.6%	5.0%	7.0%	9.3%	11.2%
	11 to 15	4.2%	5.5%	5.8%	6.5%	9.8%	11.7%
	16 to 20	4.6%	5.4%	6.5%	6.2%	9.2%	12.2%
	21 to 25	4.7%	5.1%	6.8%	6.6%	8.1%	10.5%
	26 to 30	5.2%	5.1%	6.4%	7.2%	7.4%	9.4%
	31 to 35	8.6%	4.7%	6.6%	7.6%	7.3%	8.4%
	36 to 40	9.3%	5.6%	6.4%	7.0%	7.8%	8.6%
	All Experience Levels	**4.9%**	**4.7%**	**5.6%**	**6.7%**	**8.5%**	**10.2%**
College Graduates	1 to 5	3.1%	3.8%	4.4%	7.1%	11.8%	11.8%
	6 to 10	4.1%	6.5%	6.5%	8.9%	13.7%	18.8%
	11 to 15	4.6%	6.2%	8.4%	9.2%	14.6%	18.2%
	16 to 20	4.4%	5.7%	10.0%	8.9%	13.3%	17.5%
	21 to 25	5.4%	5.5%	8.4%	9.9%	11.4%	15.5%
	26 to 30	6.7%	5.5%	7.3%	11.1%	10.4%	13.8%
	31 to 35	8.4%	6.4%	7.3%	9.4%	11.0%	11.4%
	36 to 40	10.1%	7.2%	6.9%	8.9%	13.4%	12.4%
	All Experience Levels	**5.2%**	**5.7%**	**7.1%**	**9.0%**	**12.5%**	**15.3%**

Note: Sample and method of construction of hours worked are described in the text. The data are from Ruggles et al. (2008)

Table A2:
Weekly Wages of U.S. Natives in Constant 2000 U.S. $ by group, 1960-2006
Pooled Male and Female

Group		Year					
Education	**Experience**	**1960**	**1970**	**1980**	**1990**	**2000**	**2006**
No High School Degree	1 to 5	304	360	336	265	280	266
	6 to 10	417	514	474	400	413	394
	11 to 15	480	581	527	460	471	463
	16 to 20	507	601	578	495	511	503
	21 to 25	507	624	611	521	540	527
	26 to 30	507	637	624	557	561	548
	31 to 35	506	617	644	578	577	527
	36 to 40	510	604	646	580	597	522
	All Experience Levels	**485**	**589**	**562**	**485**	**489**	**474**
High School Graduates	1 to 5	395	472	453	377	382	357
	6 to 10	523	642	572	501	509	493
	11 to 15	580	709	640	572	569	564
	16 to 20	609	730	702	613	627	623
	21 to 25	628	739	720	640	658	644
	26 to 30	623	742	734	681	673	675
	31 to 35	621	750	738	687	679	674
	36 to 40	620	741	738	676	691	649
	All Experience Levels	**568**	**679**	**635**	**580**	**601**	**591**
Some College Education	1 to 5	477	565	507	452	451	428
	6 to 10	620	768	656	605	603	593
	11 to 15	704	865	765	698	703	698
	16 to 20	744	914	839	755	769	760
	21 to 25	769	946	860	815	808	795
	26 to 30	757	961	883	858	835	831
	31 to 35	748	940	886	856	863	823
	36 to 40	743	871	884	839	867	814
	All Experience Levels	**690**	**825**	**723**	**698**	**728**	**717**
College Graduates	1 to 5	613	787	645	685	720	687
	6 to 10	804	1041	869	927	979	987
	11 to 15	937	1235	1116	1097	1259	1252
	16 to 20	1037	1350	1258	1212	1386	1422
	21 to 25	1060	1423	1336	1345	1392	1467
	26 to 30	1042	1404	1357	1386	1412	1446
	31 to 35	1065	1353	1350	1400	1491	1423
	36 to 40	1044	1278	1299	1358	1462	1451
	All Experience Levels	**926**	**1199**	**1048**	**1111**	**1245**	**1270**

Note: Sample and method of construction of weekly wages (in constant 2000 U.S. $) are described in the text. The data are from Ruggles et al. (2008).

Table A3:
Relative Weekly Wages of Foreign-Born/ US-Born Workers by group, 1960-2006
Pooled Male and Female

Group		Year					
Education	**Experience**	**1960**	**1970**	**1980**	**1990**	**2000**	**2006**
No High School Degree	1 to 5	1.09	1.05	1.03	1.13	1.18	1.10
	6 to 10	0.98	0.96	0.90	0.90	0.93	0.87
	11 to 15	1.01	1.03	0.91	0.89	0.91	0.81
	16 to 20	1.01	1.00	0.90	0.90	0.93	0.82
	21 to 25	1.05	0.99	0.91	0.90	0.89	0.81
	26 to 30	1.03	0.99	0.90	0.88	0.86	0.79
	31 to 35	1.07	1.04	0.88	0.87	0.85	0.83
	36 to 40	1.07	1.01	0.91	0.90	0.82	0.84
	All Experience Levels	**1.04**	**1.01**	**0.91**	**0.92**	**0.92**	**0.86**
High School Graduates	1 to 5	0.98	1.01	0.95	0.98	0.98	0.95
	6 to 10	0.94	0.98	0.92	0.94	0.92	0.86
	11 to 15	0.93	0.99	0.92	0.92	0.91	0.84
	16 to 20	1.03	0.98	0.91	0.96	0.91	0.83
	21 to 25	1.01	0.98	0.92	0.97	0.89	0.86
	26 to 30	1.07	1.02	0.92	0.92	0.92	0.85
	31 to 35	1.04	1.05	0.92	0.94	0.93	0.83
	36 to 40	1.04	1.00	0.96	0.96	0.91	0.89
	All Experience Levels	**1.02**	**1.00**	**0.93**	**0.95**	**0.92**	**0.86**
Some College Education	1 to 5	0.93	0.96	0.96	1.02	1.02	0.99
	6 to 10	0.92	0.94	0.95	0.98	0.97	0.93
	11 to 15	0.94	0.98	0.95	0.96	0.95	0.91
	16 to 20	0.96	0.95	0.92	0.98	0.95	0.95
	21 to 25	1.03	0.93	0.94	0.97	0.95	0.90
	26 to 30	1.04	0.87	0.91	0.95	0.96	0.93
	31 to 35	1.02	1.06	0.92	0.96	0.94	0.90
	36 to 40	1.04	1.11	0.97	0.98	0.92	0.94
	All Experience Levels	**1.01**	**0.96**	**0.94**	**0.98**	**0.96**	**0.93**
College Graduates	1 to 5	0.96	0.92	0.98	0.99	1.15	1.08
	6 to 10	0.85	0.89	0.98	0.93	1.06	1.03
	11 to 15	0.93	0.93	0.99	0.95	0.97	0.98
	16 to 20	0.95	0.94	0.99	1.02	0.94	0.92
	21 to 25	1.02	0.97	0.98	1.01	0.96	0.89
	26 to 30	1.04	0.89	1.01	1.00	0.99	0.90
	31 to 35	0.88	0.93	0.97	0.99	1.00	0.89
	36 to 40	0.96	1.05	0.95	0.99	0.96	0.97
	All Experience Levels	**0.96**	**0.93**	**0.98**	**0.98**	**1.01**	**0.96**

Note: Sample and method of construction of weekly wages (in constant 2000 U.S. $) are described in the text. The data are from Ruggles et al. (2008).

Table A4
Estimates of σ_{IMMI}, National U.S. data, 1960-2006
Wage Sample: All people who worked for wages except the self-employed, weighted by hours worked

Specification	**No Fixed Effects**	**Basic**	**Plus Time Effects**	**Plus Time by Experience effects**	**Plus Time by Education effects**	**Number of Observations**
IV (using relative employment), Men	-0.051*** (0.007)	-0.064** (0.009)	-0.032*** (0.012)	-0.070*** (0.012)	-0.004 (0.031)	192
IV (using relative employment), Women	-0.047*** (0.007)	-0.057*** (0.012)	-0.073*** (0.017)	-0.096*** (0.011)	-0.071*** (0.029)	192
1970-2006, Men	-0.044*** (0.009)	-0.062*** (0.011)	-0.032* (0.018)	-0.059*** (0.014)	-0.001 (0.033)	160
1970-2006, Women	-0.045*** (0.008)	-0.060*** (0.013)	-0.068*** (0.018)	-0.086*** (0.012)	-0.057** (0.028)	160
Less Educated Only, Men	-0.056*** (0.009)	-0.072*** (0.009)	-0.015 (0.014)	-0.015 (0.012)	-0.021 (0.035)	96
Less Educated Only, Women	-0.051*** (0.008)	-0.074*** (0.010)	-0.076*** (0.019)	-0.093*** (0.008)	-0.103*** (0.028)	96
Young Workers Only, Men	-0.035*** (0.009)	-0.045*** (0.010)	-0.063** (0.023)	-0.074*** (0.019)	0.003 (0.039)	96
Young Workers Only, Women	-0.027** (0.012)	-0.038** (0.018)	-0.092*** (0.020)	-0.098*** (0.020)	-0.098*** (0.031)	96
Fixed Effects Included:						
Education by Experience effects (32 in total)	No	Yes	Yes	Yes	Yes	
Year Effects (6 in total)	No	No	Yes	Yes	Yes	
Year by Experience Effects (56 in total)	No	No	No	Yes	Yes	
Year by Education Fixed effects (24 in total)	No	No	No	No	Yes	

Note: This table presents the same specifications as rows 4, 5, 6 and 7 of Table 2 and estimates them on the sample of men and women (separately) rather than on the pooled sample as in Table 2.
In parenthesis we report the heteroskedasticity-robust standard errors, clustered over the 32 education-experience groups.
***= significant at 1% level; **=significant at 5% level; *= significant at 10% level.

Table A5
Estimates of ($-1/\sigma_{HL}$), ($-1/\sigma_{HH}$), and ($-1/\sigma_{LL}$) CPS, U.S. data 1963-2006, Katz and Murphy (1992) Method, Men Only

	Estimates of $-1/\sigma_{HL}$	**Estimates of $-1/\sigma_{LL}$**	**Estimates of $-1/\sigma_{HH}$**	**Number of Observations**
Men Only with "Some College" split between H and L	-0.60*** (0.062) [0.077]	-0.030 (0.017) [0.018]	-0.11 (0.09) [0.11]	44
Men Only with "Some College" in H	-0.37*** (0.06) [0.08]			44
Men Only Employment as a Measure of Labor Supply	-0.72*** (0.07) [0.09]	-0.037* (0.019) [0.020]	-0.04 (0.10) [0.12]	44
Men Only 1970-2006	-0.58*** (0.07) [0.09]	0.008 (0.025) [0.027]	-0.09 (0.09) [0.10]	36

Note: Variables, definitions and regressions as in Table 6. The only difference is that the sample used to construct wages is limited to men only. In brackets are the heteroskedasticity-robust 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.