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Immigration Accounting:
U.S. States 1960-2006

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Non-Technical Abstract

Different U.S. states have been affected by immigration to very different extents in recent years. Immigration increases available workers in a state economy and, because of its composition across education groups, it also increases the relative supply of less educated workers. However, immigration is more than a simple labor supply shock. It brings differentiated skills and more competition to the labor market and it may induce efficient specialization and affect the choice of techniques. Immigrants also affect investments, capital accumulation, and the productivity of more and less educated workers. Using a production function-based procedure and data on gross state product, physical capital and hours worked we analyze the impact of immigration on production factors (capital, more and less educated labor), and productivity over the period 1960-2006 for 50 U.S. states plus D.C. We apply growth accounting techniques to the panel of states in order to identify the changes in factors and productivity associated with immigration. To identify a causal impact we use the part of immigration that is determined by supply shifts in countries of origin and the geographical location of U.S. states or historical immigrants' settlements. We find that immigration significantly increased the relative supply of less educated workers, that it did not affect much the level of capital per worker and that it significantly increased the productivity of highly educated workers and, even more, less educated workers. These channels together explain the small effect of immigrants on wages of less educated workers and the significant positive effects on wages of more educated workers.

Key Words: Immigration, Investment, Supply of skills, Productivity of workers, US States.

JEL Codes: F22, J61, R11.

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Different U.S. states have been affected by immigration to very different extents in recent years. Immigration increases available workers in a state economy and, because of its composition across education groups, it also increases the relative supply of less educated workers. However, immigration is more than a simple labor supply shock. It brings differentiated skills and more competition to the labor market and it may induce efficient specialization and affect the choice of techniques. Immigrants also affect investments, capital accumulation, and the productivity of more and less educated workers. Using a production function-based procedure and data on gross state product, physical capital and hours worked we analyze the impact of immigration on production factors (capital, more and less educated labor), and productivity over the period 1960-2006 for 50 U.S. states plus D.C. We apply growth accounting techniques to the panel of states in order to identify the changes in factors and productivity associated with immigration. To identify a causal impact we use the part of immigration that is determined by supply shifts in countries of origin and the geographical location of U.S. states or historical immigrants' settlements. We find that immigration significantly increased the relative supply of less educated workers, that it did not affect much the level of capital per worker and that it significantly increased the productivity of highly educated workers and, even more, less educated workers. These channels together explain the small effect of immigrants on wages of less educated workers and the significant positive effects on wages of more educated workers.

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1 Introduction

The most common way to analyze immigration and its effects on productivity and labor markets is to consider it as an increase in the labor supply. Most of the traditional analyses of the impact of immigrants on wages and employment at the national or local (city, state) level consider other production factors (capital, technology, efficiency) as given when analyzing the effect of immigrants. Some recent papers, however, suggest that immigration may induce changes that also affect productivity, efficiency and capital accumulation and these should be accounted for when evaluating the impact on labor productivity. First of all, besides an increase in total available workers, immigration implies an increase in the relative supply of less educated workers. As noted in several papers by Card (2001, 2007) and Card and Lewis (2007) neither the absolute nor the relative shift in employment seems to be offset by movements of the native population, and as a result there is an increase in total employment and an increase in the relative supply of less educated workers in cities and states with large immigration flows. Lewis (2005) shows that because the production techniques that are adopted locally adjust to the supply of local factors, the larger relative availability of less educated workers induces a choice of more efficient technologies. Peri and Sparber (2008) document that, because of comparative advantages, less educated immigrants supply mostly manual and physical skills thereby pushing natives to specialize towards communication tasks. This implies gains from specialization and increased overall efficiency. Moreover, greater competition from immigrants, who typically enjoy less labor market protection and may have worse outside options may induce native workers to increase their effort and efficiency driving their productivity up rather than reducing their wages. The existence of hard working immigrants in some occupations may lead to emulation and positive peer effects such as those pointed out by Mas and Moretti (Forthcoming). More generally, agglomeration and density externalities could benefit from the presence of immigrant workers who often live and work in urban areas. Finally, as described in Ottaviano and Peri (2008) physical capital accumulation will respond to the increased return to capital driven by the larger availability of labor, and hence investments will keep up with immigration even in the short run. As a result, we can consider immigration as generating an investment response. All these recent contributions imply that analyzing immigration's impact on the marginal productivity of workers given fixed capital, technology and efficiency may miss a large part of their effects. Immigrants may increase (or decrease) the productivity of similar workers, affect the choice of techniques, and affect capital accumulation, on top of their effect as a pure shifter of the labor supply. The present paper takes this broader approach and uses data on gross state product, state physical capital, state employment, hours worked and wages to analyze the impact of immigration over the period 1960-2006 on all production factors across U.S. states. In particular, with the help of a simple and popular production function framework applied to U.S. states we use the variation in immigrant inflows by countries of origin interacted with the historical presence in U.S. states or with the geographical location of U.S. states to study the impact of an immigration

shock on total labor supply, on the relative supply of more and less educated workers, on capital per worker and on specific productivity of more and less educated workers.

Besides accounting for the effect of immigration on capital, labor and productivity our method allows us to infer the impact of immigrants on the marginal productivity of labor without using data on wages, but only on output per worker, capital and labor supply (and the production function). We can also identify the importance of each channel in determining labor productivity, namely its effects on capital intensity, on unskilled labor productivity, on skilled labor productivity and on the relative supply of more and less educated workers. We then check, using individual Census data and constructing average wages for more and less educated workers by state and year whether those simulated impacts correspond to those obtained when using reduced-form regressions of wages on immigration flows. Our empirical analysis shows a remarkable qualitative and quantitative correspondence between the simulated and the estimated effect of immigration on wages. What we gain is the ability to explain, or at least decompose, the effect of immigration on the wages of more and less educated workers. The following four results are the main contribution of the paper. First, confirming most of the area literature (Card 2007, Kugler and Yuskel 2006, Ottaviano and Peri 2007) we find a very small effect of immigration on the wages of less educated (high school or less) workers. This is in spite of a significant effect of immigration in increasing the relative supply of less educated workers across states. The accounting approach reveals that this is due to the fact that productivity gains, especially for the less educated (probably driven by specialization, competition and slowing of the skill-biased technology adoption) balance the adverse effect of relative supply. Second, the wages of the more educated (some college and more) increase (+0.3% for each 1% increase in employment due to immigrants). This is due to the combination of two effects working in the same direction: immigration generates a relative supply effect in favor of highly educated workers and induces higher efficiency of this group. Third, the average wage in a state also increases significantly in response to immigrants because of productivity increases and because physical capital adjusts almost fully in order to absorb the increased labor (due to immigrants), keeping capital intensity fairly constant. Finally, capital adjustment in response to immigration seems to work fairly rapidly and fully, so that capital per worker remains essentially constant in response to a decennial inflow of immigrants. The accounting exercise shows that the productivity response to immigration is positive, significant and fairly robust. There is also some evidence that it affects the productivity of less educated workers somewhat more than that of more educated workers. These results and the explanation are in line with the positive average wage effects of immigrants estimated across cities by Card (2007) and across states by Ottaviano and Peri (2007) and Kugler and Yuskel (2006). The novelty of this paper is that we use a production function-based "accounting" procedure and data on Gross State Product (GSP) and physical capital, rather than on individual wages, to analyze changes in the marginal productivity of labor due to immigration.

The rest of the paper is organized as follows: Section 2 presents the data on the evolution of immigrant employment in U.S. states and its effect on total labor supply in the state and on the relative supply of more and less educated workers. We also identify the portion of immigration which is correlated with country of origin supply-shocks and use it, interacted with historical settlement and geographical location of states, to produce a supply-driven measure of immigrants. Section 3 presents the theoretical framework (production function-based) that allows us to use Gross State Product and data on capital, hours worked and share of wage income to construct measures of productivity for more and less educated workers. Section 4 introduces the data on Gross State Product and physical capital per worker in each state between 1960 and 2006 and empirically analyzes the impact of supply-driven immigration on them. In section 5 we construct the measures of productivity of highly educated workers (A_H) and productivity of less educated workers (A_L) in each state 1960-2006 and again we analyze how immigration affects them. Section 6 uses the measures of factors and productivity to calculate the real wage of more and less educated workers and simulates the effects due to the actual immigration 1990-2006. We then present some counter-factual simulations and we compare the simulated effect of immigration on wages with the effects estimated using actual wage measures from the Census. Section 7 provides some concluding remarks.

2 Immigration and its Effect on Labor Supply

A detailed description of the employment and wage data, the exact specification of the samples and a step-by-step description of how each variable has been constructed can be found in Appendix A. 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 (King et al., 2008). In particular, we use the general 1% sample for Census 1960, the 1% State Sample, Form 1, for Census 1970, the 1% State sample for the Censuses 1980 and 1990, the 1% Census Sample for year 2000 and the 1% sample of the American Community Survey (ACS) Sample for the year 2006. Since they are all weighted samples we use the variable “personal weight” to produce the average and aggregate statistics below. To produce measures of hours worked (or employment) and average wages by state and level of education we select the following sample. We include people aged 17 and older in the census year (corresponding to 16 and older the previous year¹) not living in group quarters, who worked at least one week in the previous year, received positive wage income and were not self-employed and we select only workers with experience of at least one year and less than or equal to forty years². We divide workers into the two education groups H (those with some college education and more) and L (those with high school education

¹Sixteen years of age is the cut-off chosen by the Bureau of Labor Statistics for those people who are defined as “working age”.

²Experience is 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.

or less) using the variable EDUCREC which classifies levels of education consistently across censuses and ACS data. The choice of considering two education groups only and the decision to split them by including high school graduates among the less educated is important and deserves some comment. First of all this is in line with most of the labor literature (from Katz and Murphy, 1992 to Autor, Katz and Krueger, 1998 and Krusell et al. 2000) that identifies people with some college or more as highly educated and estimates a significant degree of imperfect substitutability between the two groups but not among workers within each of the two groups. Second, Ottaviano and Peri (2008) clearly show that the substitutability between workers in H and L is much lower than the substitutability between workers with no degree and a high school degree within L or between those with some college and college graduates within H . In particular, the elasticity of substitution across groups is between 1.5 and 2 while within groups (between subgroups) it is often indistinguishable from infinity. Hence we follow the split that leaves the most homogenous workers within each group. The status of “foreign-born” is given to those workers who are non-citizens or are naturalized citizens (using the variable “CITIZEN” beginning in 1970 and “BPLD” 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 A for the exact definition and computational procedure) and individual hours are multiplied by the individual weight (PERWT) and aggregated within each education-state group. This measure of hours worked by education group and state is the basic measure of labor supply. We call H_{st}^D and H_{st}^F the hours worked, respectively, by domestic (native) and foreign highly educated workers in state s and year t so that $H_{st} = H_{st}^D + H_{st}^F$ is the total of hours worked by highly educated workers in state s and year t . Similarly, we call L_{st}^D and L_{st}^F the hours worked, respectively, by domestic (native) and foreign less educated workers in state s and year t so that $L_{st} = L_{st}^D + L_{st}^F$ is the total of hours worked by less educated workers in state s and year t . Finally, consistently with the model below, let us call $N_{st} = N_{st}^D + N_{st}^F$ total hours supplied by workers of both education levels (sum of H and L) in state s and year t .

2.1 Effect of Immigration on Total Hours Worked

Let us first provide an illustration of the differences in the inflow of immigrants (and immigrants as share of total labor) across U.S. states over the 1960-2006 period. Figure 1 shows the cumulated growth of labor supply (hours worked) due to immigrants, standardizing total hours worked in the state in 1960 to 1. We report with red lines the five states that experienced the largest inflow of immigrants as a percentage of initial employment (they were Nevada, California, Florida, Arizona and Texas) and with blue lines the five states with the smallest immigration as a percentage of initial employment (North Dakota, Vermont, West Virginia, Maine and Montana). The average for the U.S. is represented by a solid black line. The graph represents the variable $(N_{st}^F - N_{s1960}^F)/N_{s1960}$ for $t = 1970, 1980, 1990, 2000$ and 2006. Correspondingly, Map 1 shows states in the U.S. with color intensity proportional to the variable $(N_{s2006}^F - N_{s1990}^F)/N_{s1990}$, the recent immigration relative

to 1990 total hours worked while Map 2 shows color intensity proportional to the 2006 share of immigrants in labor supply (hours worked), i.e., (N_{s2006}^F/N_{s2006}) . Two things should be emphasized. First, there are very large differences in immigration rates across states. While the "bottom states" received net inflow of immigrants over 46 years that amounts to only a few percentage points of their 1960 employment (between 0 and 5%), the top states received a net inflow sometimes larger than 60% of the 1960 employment. Second, comparing Maps 1 and 2 one notices a very large overlap between states with large recent net immigration 1990-2006 and states with a currently large share of immigrant-supplied labor. This is not surprising as the current stock of immigrants is in part the result of the recent flows of immigrants and a large immigrant population, in turn, attracts new immigrants. The high immigration states are mainly aligned over the Mexican border extending to the west coast, plus around New York City and Florida. This suggests that the location of a state (near the border or near Los Angeles, New York or Miami, the three main ports of entry for international travellers³) interacted with the increase in immigrants from Latin and Central America (through the Mexican border or Miami) and Asia (through Los Angeles and New York) provided an asymmetric exposure to immigration flows. These supply and geography-driven differences in immigration rates across states can be exploited in order to identify the net immigration flows to a state that are unrelated to demand and local economic factors but rather are determined by push factors from countries of origin and distance from ports of entry. Following Card (2001), Card and Lewis (2007) and Peri and Sparber (2008) we isolate the supply-driven component of $(N_{st+10}^F - N_{st}^F)/N_{st}$, the immigration in state s over decade t , using two methods. First, we impute the working-age population of foreign born in year t using the immigrant working-age population in 1960 separated into ten world regions of origin (see Appendix B) and we augment each group by the national growth rate of the population from that region of origin between 1960 and t . So, defining such imputed immigrant population as $\widehat{POP}_{s,t}^F$ we instrument $(N_{st+10}^F - N_{st}^F)/N_{st}$ with $(\widehat{POP}_{s,t+10}^F - \widehat{POP}_{s,t}^F)/(\widehat{POP}_{s,t}^F + POP_{s,t}^D)$. Alternatively, to avoid altogether the use of the initial distribution of immigrants by state, which may be correlated with economic conditions in 1960, we proxy $(N_{st+10}^F - N_{st}^F)/N_{st}$ with its predicted value from a regression on log distance from the border, from Los Angeles, from Miami and from New York, interacted with decade dummies. Since total immigration flows and the importance of ports of entry changed over time the interactions allow us to capture variation across states and decades. For instance, the large Mexican migration in the 90's (but not in the 60's) implies a large (negative) correlation of the instrument "distance from the border" interacted with the 90's dummy with immigration by states, but a much smaller correlation when the border distance is interacted with the 60's dummy. Hence we use these two instruments, imputed immigrants and geographic variables by decade, to identify the effect of a supply-driven change in immigration in a state. Essentially, the identifying variation that determines the effect

³These data are from the U.S. Department of Commerce, ITA, Office of Travel & Tourism Industries, Summary of International Travel to the U.S. (I-94) report, 2007 available at <http://tinnet.ita.doc.gov/view/m-2007-I-001/index.html>.

of immigrants is similar to a difference in difference method. We exploit differences between states near or far from the border (and from ports of entry) and compare them in decades before and after the large increase in flows from Mexico-Latin America and East Asia around the mid-eighties.

The first important issue to settle regarding the use of these data is whether immigrant inflows have a net effect on the local labor supply or are offset by corresponding opposite outflows of natives. Do immigration states show faster employment growth because of immigration or does immigrant employment growth simply substitute for native employment growth? A look at the data helps to get a sense of the correlations involved. Figure 2 shows for the same top and bottom immigration states in Figure 1 the total growth of hours worked as a % of hours worked in 1960. Two striking features emerge. First, the high immigration (red) states are also high employment growth states (all above the U.S. average) and the low immigration states are also low employment growth states (all are below the U.S. average). Second, the differences in growth of total hours worked between states are much larger than differences in immigration (relative to hours worked). Even in large immigration states immigrants were only small contributors, over the 1960-2006 period, to employment growth. This is true not only of the growth rate of hours worked but also of their variation across states. Figure 3 shows the scatter-plot of $(N_{st+10} - N_{st})/N_{st}$, the decade percentage growth of hours worked by state over the 1960-2006 period, against $(N_{st+10}^F - N_{st}^F)/N_{st}$, the portion of the increase due to immigrants. Again it is evident that the variation in total employment growth is much larger than the variation in immigrant-driven employment growth (look at the range of the vertical axis against the range of the horizontal one). Nevertheless, the regression line estimated is positive, significant and its slope is larger than one (1.55). A slope of 1 would imply that the whole inflow of immigrants translate into employment growth with no offsetting change from native employment. However, it is very likely that a good part of the positive correlation between growth in hours worked and immigration is driven by some state-specific labor demand factor that caused both. Hence it helps to have a more systematic econometric approach to the effect of immigration on employment. Following a large part of the literature (e.g., Card 2001, Card and Lewis 2007 and Ottaviano and Peri 2007) we consider the following regression:

$$\frac{N_{st+10} - N_{st}}{N_{st}} = D_t + \theta \frac{N_{st+10}^F - N_{st}^F}{N_{st}} + \varepsilon_{st} \quad (1)$$

where D_t are decade-specific effects, the parameter θ is the elasticity of total hours worked to immigrant-supplied hours worked and ε_{st} is a random disturbance, potentially correlated within states but not across states. The literature interprets a value of θ equal to one as evidence that there is no offsetting change in native employment in response to immigration and thus immigrants are a net addition to the local labor force. However, to avoid the possibility that demand factors specific to the state and decade might affect total employment (through ε_{st}) and at the same time attract immigrants, generating a correlation between explanatory variables

and residuals, we need to instrument the immigrants inflow with the imputed immigrant variable and the geographic distance variables. Table 1 shows the estimated θ coefficients, first simply using weighted least squares⁴ (in specifications 1 and 2) and then performing 2SLS estimation using geographic instruments only (3) or imputed immigrants and geographic instruments together (4). Finally, in the last specifications (5) we perform 2SLS while controlling for the lagged change in employment, $\frac{N_{st}-N_{st-10}}{N_{st-10}}$ in order to capture any persistence in the performance of employment growth. Two important results emerge very clearly from Table 1. First the WLS estimates of θ (equal to 1.68 and 1.64) are substantially larger than the 2SLS estimates (between 0.87 and 1.18), suggesting that omitted demand shocks bias upward the estimate of θ . Second, the more reliable 2SLS estimates are around one and can never reject one as the estimated value. This is consistent with no offsetting employment change by native workers and implies that immigration increases one for one the total hours worked in a state. One thing to notice, common to least squares and 2SLS regressions, is the large imprecision of the estimates. This is not due to weakness of the instruments which, as shown in the last two rows of Table 2, are quite strong (especially when used jointly) producing an F-test of joint significance equal to 30 or more. It is due, instead, to the much larger variance of the dependent variable (hence of ε_{st} in our specification) relative to the explanatory variable (as seen in Figure 3). The fact that with small variation in the explanatory variable the standard deviation of the estimate $\hat{\theta}$ is large is a well-known fact⁵.

Table 2 confirms the results of Table 1. It shows that if we regress the change in hours worked by natives only $\frac{N_{st+10}^D - N_{st}^D}{N_{st}}$ on the change due to immigrants $\frac{N_{st+10}^F - N_{st}^F}{N_{st}}$, otherwise reproducing the specifications and methods in columns (1) to (4) of Table 1, we obtain positive values when using weighted least squares and insignificant (still positive) values when using 2SLS. There is no evidence of a negative response in the employment of natives, and using 2SLS not much evidence of spurious positive correlation either. All in all, these results amount to reasonable evidence that immigration in aggregate does not crowd out native employment and that our geographic and imputed immigrants instrumental variables avoid the spurious positive employment effects from demand shocks.

2.2 Effects of Immigration on Relative Supply of Less Educated Workers

The second effect of immigrants on the local labor supply is a potential tilting of workers' composition towards the less educated. Immigrant workers are more likely to have a high school education or less compared to native workers. For instance, in 2006 48% of immigrant workers had a high school degree or less, while the corresponding percentage among natives was 36%. In most states, as of 2006, immigrant workers were disproportionately less educated relative to natives. Figure 5 plots the share of less educated immigrant workers against the corresponding share for natives across states in 2006. Most points, and certainly all points corresponding to the

⁴The weights are equal to employment in the state-year and correct for differences in measurement error.

⁵See for instance Greene (1993), page 156.

large immigration states, are above the 45 degree line implying a larger share of less educated among immigrants in most states. Hence, a larger immigrant population may correspond to a larger relative supply of less educated workers. The same question we confronted with respect to total employment, however, applies here as well. Does the internal migration response of natives offset this tilt? It could be the case that even with no overall effects on employment, natives in a state respond to international migrants via the flight of less educated natives and the immigration of more educated natives, re-establishing pre-migration relative supply.

Let us begin, again, with a look at the top and bottom immigration states. Figure 5 shows that, with the exception of West Virginia which appears to be an outlier, the high immigration states had a smaller cumulated decline over the 1960-2006 period in the share of labor supplied by less educated workers than the low immigration states did. We can see that the red lines are all above the average U.S. line and the blue lines (except for West Virginia) are all below. Such behavior, however, as clarified by Figure 6, is not due to a systematic change of the share of less educated workers within the native population. Except for the outlier West Virginia, the decline in the share of less educated native workers is comparable in high and low immigration states. Hence the preliminary evidence suggests that the effect of immigrants is to tilt the relative labor supply towards the less educated, without a countervailing offset in native relative supply.

In Tables 3 and 4 we present more systematic evidence of this. Table 3 shows the estimates of the parameter ϑ from the following regression:

$$(l_{st+10} - l_{st}) = D_t + \vartheta \frac{N_{st+10}^F - N_{st}^F}{N_{st}} + u_{st} \quad (2)$$

The dependent variable is the change in the share of hours worked by less educated workers during the decade. D_t are decade dummies and u_{st} random disturbances. Specifications (1) and (2) in Table 3 report weighted least squares estimates, while (3) and (4) report the 2SLS estimates. The 2SLS coefficients imply that an increase of immigrants equal to 1% of initial employment produces an increase in the share of hours worked by less educated workers in the state by around 0.25%. Now the 2SLS coefficients are larger than the least squares, and their estimates are rather precise. The scatter-plot in Figure 7 is the graphic representation of the regression in specification (1) of Table 3. Namely, once we control for decade dummies, it shows a very significant partial correlation between the net flow of immigrants and the change in the share of less educated workers. Table 4 then shows how the significant effect on the share of less educated workers is not due at all to a change in the native share of less educated workers. The coefficients estimated in Table 4 are from a regression of $(l_{st+10}^D - l_{st}^D)$ on $\frac{N_{st+10}^F - N_{st}^F}{N_{st}}$ in a specification otherwise identical to (2). Their values, never significantly different from 0, show that the relative composition of native workers between more and less educated is not affected at all by immigration. Natives neither respond to the unbalance with selective migration out of the state, nor there is a significant positive correlation between immigration and natives' skill composition which would be

a potential sign of omitted demand factors. Figure 8 is the graphic representation of the partial correlation estimated in column (1) of Table 4.

In summary, the data suggest that immigration has been an supply shock to total employment and the relative skill composition of workers and that it was very uneven across U.S. states. A large part of this unevenness is correlated with the large push-driven migration from Central America and Asia interacted with the location of states (relative to the border or the main ports of entry to the U.S.). At the same time these uneven shocks resulted in faster employment growth and slower reduction of the share of less educated workers in states with large immigration rates. This was directly due to the effect of immigrants, as the employment growth and skill composition of natives was not affected by the intensity of immigration. Having described the effects of immigrants on total and relative labor supply let us now analyze their effects on other production factors and on technology and efficiency. To do this we will develop a simple production function-based framework.

3 Production Function Framework

Following a popular approach in the Labor and Macro literature⁶ we combine physical capital and workers of different levels of education in a production function. In particular consider each state s of the U.S. in each year t as producing a homogenous, perfectly tradeable output, using the following production function that expresses output and inputs per unit of labor:

$$y_{st} = k_{st}^{\alpha} \left[(A_H h)_{st}^{\frac{\sigma-1}{\sigma}} + (A_L l)_{st}^{\frac{\sigma-1}{\sigma}} \right]^{(1-\alpha)\frac{\sigma}{\sigma-1}} \quad (3)$$

The subscript $s = 1, 2, \dots, 51$ refers to a state and $t = 1960, 1970, 1980, 1990, 2000, 2006$ refers to the considered year. The variable $y_{st} = Y_{st}/N_{st}$ measures total output (Y_{st}) per unit of labor (N_{st}) that we assume to be measured (as in the empirical analysis) by hours worked. The variable $k_{st} = K_{st}/N_{st}$ measures physical capital services per unit of labor and $h = H_{st}/N_{st}$ and $l = L_{st}/N_{st}$ represent the share of total hours worked supplied by workers with high levels of education (H) and by workers with low levels of education (L), respectively. Hence, by construction $h + l = 1$. The terms A_H and A_L represent the productivity specific to more and less educated workers. Since both the factor supply and productivity terms have subscripts s, t the representation above allows each state to have a technology that may be biased towards (specific to) the type of workers that are more abundant in its labor force. In such an aggregate production function differences in technology A_H and A_L may arise because of differences in sector specialization or because of differences in technologies within sectors. The parameter σ measures the elasticity of substitution between more and less educated workers and α captures the elasticity of output with respect to physical capital.

⁶E.g., Katz and Murphy (1992) and Caselli and Coleman (2007).

The production function above is significantly simpler than the one used in Ottaviano and Peri (2008) in which we also allowed imperfect substitution between native and immigrant workers and between different experience groups. The focus of this paper is on overall effects (not differentiating between natives and older immigrants) and the relatively large elasticity between the two groups estimated in Ottaviano and Peri (2008) (around 20) implies that in this context the assumption of perfect substitutability between natives and immigrants is a convenient and not crucial simplification. Hence, as already described above we assume that total hours worked by less educated workers can be expressed as $L = L^F + L^D$ and hours worked by highly educated workers can be expressed as: $H = H^F + H^D$. Similarly, we omit the partition across experience groups since we are not interested in deriving results specific to the wages of younger or older workers. Finally, the choice of two education groups, identified as those with a high school diploma or less (L) and those with at least some college education (H) or more, is justified by the ample evidence, reported in Ottaviano and Peri (2008), that while there is imperfect substitutability between workers in these two groups (with an elasticity σ close to 1.75) workers of different education within each of those two groups (e.g., those with no high school degree and those with a high school degree) appear to be highly substitutable. Hence, for a more “macro” approach, as in this paper, a production function like (3) is simple, well known and maintains the key distinction between more and less educated workers without the nuances and complications of a more cumbersome multi-level CES.

One could re-state equivalently the technological parameters A_H and A_L in a Total Factor Productivity term (TFP) given by the following expression:

$$TFP = A = (A_H + A_L)^{(1-\alpha)} \quad (4)$$

where we have omitted the subscript for simplicity. Then the production function can be written as

$$y_{st} = A_{st} k_{st}^\alpha \left[(\beta h)_{st}^{\frac{\sigma-1}{\sigma}} + ((1-\beta)l)_{st}^{\frac{\sigma-1}{\sigma}} \right]^{(1-\alpha)\frac{\sigma}{\sigma-1}} \quad (5)$$

where $\beta = A_H/(A_H + A_L)$ can be interpreted as a pure skill-bias term in the productivity of a state in a year. In the standard procedure with only one productivity parameter (A) knowing the values of y_{st} , of k_{st} and the total hours worked one could back out the value of A_{st} by applying the residual method first proposed by Solow (1957). In our case, with two unknown productivity parameters A_H and A_L , we can determine these if we also know the supply of hours by each group (h_{st} and l_{st}) and the share of total wages going to each group.

Defining the wage of each type of worker as w^H and w^L , in equilibrium they equal their marginal productivity. Taking their ratio and re-arranging we obtain:

$$\frac{w^H}{w^L} = \left(\frac{A_H}{A_L} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{h}{l} \right)^{-\frac{1}{\sigma}} \quad (6)$$

Together with equation (3) the above condition on marginal productivity of workers provides two equations in the two unknown A_H and A_L , which can be solved to obtain their values as⁷:

$$(A_H)_{st} = \frac{y_{st}^{\frac{1}{1-\alpha}} k_{st}^{\frac{-\alpha}{1-\alpha}}}{h_{st}} \left(\frac{w_{st}^H h_{st}}{w_{st}^H h_{st} + w_{st}^L l_{st}} \right)^{\frac{\sigma}{\sigma-1}} \quad (7)$$

$$(A_L)_{st} = \frac{y_{st}^{\frac{1}{1-\alpha}} k_{st}^{\frac{-\alpha}{1-\alpha}}}{l_{st}} \left(\frac{w_{st}^L l_{st}}{w_{st}^H h_{st} + w_{st}^L l_{st}} \right)^{\frac{\sigma}{\sigma-1}} \quad (8)$$

Using data on y and k from the state accounts and data on hours worked by each type of worker (l_{st} , h_{st}) and their share in the wage-bill $\frac{w_{st}^H h_{st}}{w_{st}^H h_{st} + w_{st}^L l_{st}}$ and $\frac{w_{st}^L l_{st}}{w_{st}^H h_{st} + w_{st}^L l_{st}}$ from the Census we can calculate the productivity specific to each factor in each state and period. Our goal is to consider how immigration shocks (proxied by our instrumental variables) affected $(A_H)_{st}$, $(A_L)_{st}$ and k_{st} in addition to affecting l_{st} and h_{st} in the long-run (decade intervals). Once we evaluate those responses we can evaluate the effect of immigration on the marginal productivity of each group in each state. In particular the dependence of wages of more and less educated workers on the variables k , A_L , A_H , l and h is (omitting the subscripts for simplicity) as follows:

$$w_H = (1 - \alpha)k^\alpha \left[(A_H h)^{\frac{\sigma-1}{\sigma}} + (A_L l)^{\frac{\sigma-1}{\sigma}} \right]^{(1-\alpha)\frac{\sigma}{\sigma-1}} \frac{A_H^{\frac{\sigma-1}{\sigma}} h^{-\frac{1}{\sigma}}}{(A_H h)^{\frac{\sigma-1}{\sigma}} + (A_L l)^{\frac{\sigma-1}{\sigma}}} \quad (9)$$

$$w_L = (1 - \alpha)k^\alpha \left[(A_H h)^{\frac{\sigma-1}{\sigma}} + (A_L l)^{\frac{\sigma-1}{\sigma}} \right]^{(1-\alpha)\frac{\sigma}{\sigma-1}} \frac{A_L^{\frac{\sigma-1}{\sigma}} l^{-\frac{1}{\sigma}}}{(A_H h)^{\frac{\sigma-1}{\sigma}} + (A_L l)^{\frac{\sigma-1}{\sigma}}} \quad (10)$$

Such a method provides an alternative evaluation of the effect of immigration on wages. To construct w_H and w_L we use data on value added, capital and the hours supplied by each group and their share in total wage-bill, and not individual wages as most studies have done so far. Moreover, this method allows us to decompose the effect of immigration on wages. Equations (9) and (10) suggest that each wage depends on three terms. The first, $(1 - \alpha)k^\alpha$, is mostly affected by the response of capital per unit of labor to immigration. If capital does not react to increases in total labor supply due to immigration, capital per worker decreases (in the short run) and wages decrease as well. The second term, $\left[(A_H h)^{\frac{\sigma-1}{\sigma}} + (A_L l)^{\frac{\sigma-1}{\sigma}} \right]^{(1-\alpha)\frac{\sigma}{\sigma-1}}$, is mostly affected by the response of TFP to immigration. In fact while relative shifts of h and l (which always add up to one) only have second order effects, a common change in A_H and A_L (hence of TFP) is primarily what shifts this term. Finally, the third term, $\frac{A_H^{\frac{\sigma-1}{\sigma}} h^{-\frac{1}{\sigma}}}{(A_H h)^{\frac{\sigma-1}{\sigma}} + (A_L l)^{\frac{\sigma-1}{\sigma}}}$ for the wage of highly educated workers (or $\frac{A_L^{\frac{\sigma-1}{\sigma}} l^{-\frac{1}{\sigma}}}{(A_H h)^{\frac{\sigma-1}{\sigma}} + (A_L l)^{\frac{\sigma-1}{\sigma}}}$ for the wage of less educated workers) is mostly negatively affected by an increase in relative supply of the same type of workers but is positively affected by a response in productivity specific to the skill-group. In this context we can analyze which part of the wage change is due to a relative supply effect, which part is due to capital adjustment and

⁷This result was first derived by Caselli and Coleman (2006).

which part is due to technological adjustment (on average and specific to a factor).

4 Gross State Product and Physical Capital

4.1 Measures

We consider U.S. states as the relevant units (labor markets) for our analysis. Our production function-based approach implies that we should use measures of the gross product at the state level Y_{st} and of the stock of physical capital at the state level, K_{st} . The data on Gross State Product (GSP) are available from the Bureau of Economic Analysis (2008a). Using data on local labor income, local business tax and local capital income by industry and state and complementing them with value added data from the Economic Census and the Bureau of Economic Analysis produces figures on Gross State Product in current dollars. The current available series covers the period 1963-2006. We use that series and convert it to constant 2000\$ using the Implicit Price Deflators for Gross Domestic Product available from the Bureau of Economic Analysis (2008b). Finally, we extend the series backwards to 1960 using the state-specific real growth rates of GSP averaged over the 1963-1970 period to impute growth between 1960 and 1963. We only use data relative to 1960, 1970, 1980, 1990, 2000 and 2006 for the 50 states plus DC. This allows us to combine them with the measures of hours worked obtained from Census data, whose construction is described in section 2 above. The variable y_{st} , output per worker, is then constructed by dividing the real GSP by hours worked in the state.

The construction of physical capital by state is a bit more cumbersome, as the National Economic Account only estimates the stock of physical capital by industry at the national level⁸. Following Garofalo and Yamarik (2002) we use the national estimates of the capital stock over the period 1963-2006 for 19 industries (listed in Appendix C). We then distribute the national capital stock in a year for each industry across states in proportion of the value added in that industry generated in each state. This assumes that industries operate at the same capital-output (and capital-labor) ratios across states, hence deviation of the capital stock from its long-run level for an industry is similar across states because capital mobility across states ensures equalization of capital returns by industry. Essentially, the state composition across industries and the adjustment of the capital-labor ratio at the industry level determine in our data the adjustment of state capital-labor ratios. We then deflate the value of the capital stocks using the implicit capital stock price deflator available from Bureau of Economic Analysis (2008b) and we extend the stock backward for each state to 1960, applying the average growth rate between 1963-1970 to the period 1960-1962. This procedure gives us a panel of real capital stock values by state and year that we call \tilde{K}_{st} . To obtain K_{st} , the flow of yearly capital services entering the production function, it make sense to multiply the calculated stock by the average number of hours that it is used in a year. Assuming

⁸See Appendix C for details.

that people at work use the capital stock we can define the yearly flow of capital services as $K_{st} = \tilde{K}_{st} * \overline{hours}_{st}$ where \overline{hours}_{st} measures the average hours worked by an employee in state s in year t . Therefore, the capital services per unit of labor ($k_{st} = K_{st}/N_{st}$) can also be calculated as the ratio of the capital stock \tilde{K}_{st} divided by employment E_{st} . Hence k_{st} can be called the stock of capital per worker, or equivalently the flow of capital services per unit of labor.

Our main goal in this section is to illustrate the effect of immigration on measures of gross state product per worker and on capital per worker. Notice that if capital and technology were not responding to immigration, decreasing returns to capital in the production function (3) would imply that capital per worker and value added per worker decrease following an increase in labor due to immigrants. As the data on GSP per worker and capital per worker have never been used in the literature on immigration, let me first present the data and some of their characteristics.

Figures 9 and 10 show the real state product per worker and real capital per worker for each state and on average during the period considered (in a logarithmic scale). The average values relative to the U.S. in logarithmic terms are those connected by a solid line between years. The average growth rate of output per worker implied by the data is 2.3% per year in the 1960's and in the 70's it decreases to 1.9% and 1.2% in the eighties and nineties (productivity slowdown) and increasing again in the last period (2000-2006) to 2.2% per year. This is in line with known national trends. Figure 9 also shows a convergence of output per worker across states (once we eliminate D.C., a small and very special economy) between 1960 and 2006. The growth rate of capital stock per worker follows a similar trend with rates of growth equal to 1.9% per year before 1980, slowing to 0.7% per year in the eighties and nineties and then re-accelerating to 1.7% per year in the 2000's. Also reassuring (and not reported in the tables) are several other checks we performed. First, a regression of changes in GSP per worker on capital per worker produces a precisely estimated coefficient around 0.32 (standard error of 0.07), which is perfectly in line with the elasticity of output to capital estimated in the literature (usually around 0.33 and equal to the value of the parameter α in our model). Moreover we also find a very strong correlation between GSP per hour worked and hourly wages (calculated from individual census data)– when we regress the first (in logs) on the second (in logs) in the panel we obtain a coefficient of 0.43 (standard error 0.03) and R^2 of 0.63. Since those two should measure average and marginal productivity of workers it is reassuring to find that they are so strongly correlated.

4.2 Effects of Immigration on Output per Worker and Capital per Worker

It is interesting to evaluate the long-run impact of immigration on output per hour worked and output per worker over decennial changes. Such an impact depends on the effect of immigration on the labor supply as well as on the response of the capital stock and technology. Output per worker is a measure of average labor

productivity and is highly correlated with average wages which reflect marginal labor productivity. Table 5 shows the estimates of the parameter ϕ from the following regression:

$$\frac{x_{st+10} - x_{st}}{x_{st}} = D_t + \phi \frac{N_{st+10}^F - N_{st}^F}{N_{st}} + e_{st} \quad (11)$$

where x_{st} is alternatively output per hour (in the first row of Table 5), hours per worker (in the second row), or output per worker (in the third row). The dependent variable is the usual measure of immigration as the decennial change in hours worked due to immigrants relative to initial hours worked. D_t are five decade fixed effects and e_{st} are random errors. Column (1) shows the weighted least squares estimates (the standard errors are always heteroskedasticity-robust and clustered by state). Columns (2) and (3) show the 2SLS estimates and Columns (4) and (5) show the 2SLS estimates controlling for the initial value of the dependent variable, x_{st} : if there is slow adjustment to other shocks, slow convergence to a long-run balanced growth path, and persistence it may be important to control for the lagged level of the dependent variable. Looking at the effect of immigration on output per worker we find quite significant positive values. While the WLS estimates can be upward biased by potential demand shocks, the 2SLS estimates range between 0.36 and 0.47. Including the initial output per worker as a control increases the estimates further to 0.48-0.78. Focussing on the 2SLS estimates of columns 3 and 4, which provide the most reasonable values and relatively small standard errors, we infer that an increase in immigrants of 10% of the initial employment over a decade is associated with an increase in output per worker in the state by 4 to 5%. This is a significant correlation, both statistically and economically. Since the 2SLS estimation is consistent with a causal interpretation one can decompose these effects further into an increase of average hours worked equal to 1% (using the second row coefficients between 0.09 and 0.10) and an increase of productivity per hour between 3 and 4% (using the coefficients in the third row which are between 0.27 and 0.37). The standard errors are somewhat large, but in the majority of cases the coefficients are significant at the 5% level. While we will be more careful in decomposing this effect, these estimates already provide the essence of our finding: states that received large inflows of immigrants, correlated with their geographic position near the border (or near ports of entry) or their historical immigrant population, also experienced faster growth of production per worker. The channels for these productivity gains, as we will speculate below, may be related to increased competition and effort among workers (corroborated by evidence of longer working hours), increased gains from specialization, choice of appropriate technologies and increased efficiency.

Then, to assess the effect of immigration on capital per worker we run the following regression across states and decades:

$$\frac{k_{st+10} - k_{st}}{k_{st}} = D_t + \beta \ln(k_{st}) + \psi \frac{N_{st+10}^F - N_{st}^F}{N_{st}} + \epsilon_{st} \quad (12)$$

The estimates of the coefficient ψ are shown in Table 6. The decennial growth of capital per worker in percentage terms is regressed on the initial (logarithmic) level of capital per worker, on five decade dummies and on immigration as a percentage of initial labor supply, allowing for zero-mean random errors ϵ_{st} . Again, the potential slow response of capital to other types of shocks and differences in the initial values of capital per worker implies that we should control for its lagged value in the regression. Columns (1) and (2) report the coefficients estimated using WLS and Columns (3) and (4) report the 2SLS estimates. While the point estimates of ψ are negative, their values are very small, especially in the 2SLS estimates (-0.01 and -0.03) and never statistically different from 0. Any long run model with capital adjustment (in a closed or open economy) predicts that in the long-run K_{st} adjusts to the evolution of labor supply N_{st} to keep its rate of return (and the capital-output ratio) constant. Moreover, U.S. states enjoy a very high degree of capital mobility between them. Hence the fact that over ten years k_{st} does not seem to be affected much by immigration shocks, implying that K_{st} fully adjusts to N_{st} , is perfectly in line with the theory and observations. On the one hand, as we showed in section 2 immigration represents only a small total employment shock in most states, relative to the changes of N_{st} due to natives; on the other hand, capital adjustment that works to equate the return to capital across states can be quite fast⁹, especially if capital is internally mobile (as it should be). Hence the estimated zero effect of decennial immigration shocks on k_{st} is perfectly in line with the theory and it is also plausible empirically.

5 Factor-Specific Productivity

5.1 Measures

The data on y_{st} and k_{st} described in the previous section plus the data on hours worked by people with a high school degree or less (l_{st}) and by those with some college or more (h_{st}) obtained from the Census data together with their share in total wage income, allow us to calculate the value of productivity A_L and A_H by state and year using the formulas 7 and 8. We also need the values of two crucial parameters to calculate A_L and A_H , namely the share of capital income α and the elasticity of substitution between more and less educated workers, σ . The good news is that these are two parameters on which there is a robust consensus in the literature. In particular, α is usually set around 0.33 (recall also that our estimate of the elasticity of output to capital was 0.32), while σ is usually estimated to be around 1.5-1.75, but is possibly as large as 2¹⁰. Caselli and Coleman (2002) choose a value of $\alpha = 0.33$ and $\sigma = 1.5$ while Caselli and Coleman (2006) choose a range of σ between 1.1 and 2 together with a production function identical to 3. Hence, we calculate A_L and A_H

⁹The speed of adjustment of capital to deviation from its balanced growth path is estimated between 10 and 20% per year at the U.S. national level. See a discussion in Ottaviano and Peri (2008).

¹⁰Estimates of σ are found in Katz and Murphy (1992), Krusell et al. (2001) and reviewed in Autor, Katz and Krueger (1997) and Johnson (1997).

under the alternative values of $\sigma = 1.5$, $\sigma = 1.75$ and $\sigma = 2$ with the idea that 2 is probably a high value and 1.75 is close to the consensus value. The advantage of obtaining a separate measure for the productivity of more and less educated workers is that, while we can still infer from them the TFP of a state (from equation 2) and the impact of immigration on it, we can also characterize the "skill bias" of the productivity responses to immigration across states. A large body of literature (from Acemoglu 2002 to Caselli and Coleman 2002) argues that the U.S. experienced a period of skill-biased technological progress during the last forty years, in the sense that technological improvements (the information and communication revolution) increased the productivity of highly educated workers more than the productivity of less educated workers. In fact they found that the productivity of less educated workers actually decreased during the eighties and nineties. Our data confirm their previous findings. Figures 10 and 11 show the behavior of $\ln(A_L)$ and $\ln(A_H)$, calculated for $\sigma = 1.75$, across states and over time, with the connecting line showing the behavior for the average U.S. value over time. First, notice the constant productivity growth of highly educated workers since 1960, with a visible period of faster growth during the eighties. The average growth of A_H over the 46 years considered was 3.8% per year. Second, notice the very different and poor performance of $\ln(A_L)$, which experienced a negative average growth of -1% per year with a remarkably faster negative growth during the eighties (a decade of significant deterioration of income distribution) of -1.7% per year. As for the relative dispersion of productivity across states, omitting D.C., the distribution of A_H seems to become tighter across states over time, confirming the idea of diffusion of technologies across states, while the dispersion of A_L seems rather stable. Reassuringly, the behavior of the average values of $\ln(A_L)$ and $\ln(A_H)$ for the U.S. shown in Figures 10 and 11 are perfectly in line with those reported in Figure 2 of Caselli and Coleman (2002) who examine yearly behavior but only over the period 1963-1992. So, in general, U.S. states experienced strong growth in the productivity of highly educated workers and a moderate decline in the productivity of less educated workers between 1960 and 2006. This is what has been designated as "skill-biased" technological progress.

5.2 Effects of Immigration on A_L and A_H

With the values of A_L and A_H (for each state s and year t) at hand we can also analyze the response of those variables (and their combination, which reflects TFP) to immigration in the long run. Table 7 reports the estimates of the coefficients ρ_L , ρ_H and ρ_{TFP} from the regressions below:

$$\frac{(A_L)_{st+10} - (A_L)_{st}}{(A_L)_{st+10}} = D_t + \rho_L \frac{N_{st+10}^F - N_{st}^F}{N_{st}} + \epsilon_{Lst} \quad (13)$$

$$\frac{(A_H)_{st+10} - (A_H)_{st}}{(A_H)_{st+10}} = D_t + \rho_H \frac{N_{st+10}^F - N_{st}^F}{N_{st}} + \epsilon_{Hst} \quad (14)$$

$$\frac{TFP_{st+10} - TFP_{st}}{TFP_{st}} = D_t + \rho_{TFP} \frac{N_{st+10}^F - N_{st}^F}{N_{st}} + \epsilon_{Tst} \quad (15)$$

As usual we consider the decennial change of the dependent variable in percentage terms regressed on decennial dummies and on the usual measure of immigration. The first three rows of Table 7 report the estimates when A_L and A_H are constructed using a value of $\sigma = 1.5$, the following three rows report coefficients for values of productivity based on $\sigma = 1.75$ and finally the last three report the estimates when $\sigma = 2$. The table shows the results of weighted least square estimation in Column 3 and then the coefficients estimated using the 2SLS method in Columns 4 and 5. Two results emerge. First, in all cases immigration is associated with a significantly positive effect on TFP. The 2SLS estimates confirm that such an effect survives the correction for demand shocks. This means that combining the effect on productivity growth of more and less educated workers (in most cases both are positive but in some cases one is negative) the overall impact on average TFP of a state was positive and significant. The point estimate of this effect is not very precise and depends in part on the assumption on σ and on the method of estimation. However, the estimates of Column (5) that use all instruments show systematically an estimated elasticity around 1. Second, using the most plausible estimates of σ (between 1.5 and 1.75) immigration seems to produce a somewhat unskilled-biased productivity effect. Due to the rather imprecise estimates of ρ_L the size of this bias is a bit hard to pinpoint. In the intermediate case of $\sigma = 1.75$ the average effect of immigration on the percentage growth of A_L is about 0.3 larger than the effect on the growth of A_H . This “unskilled-biased” direction of the effect of immigrants on productivity disappears, however, if we use $\sigma = 2$ which delivers essentially neutral effects on productivity. The unskilled-biased direction seems plausible and in line with previous findings. Immigration, as we showed in Section 2 produces a supply shift toward relatively less educated workers. Hence, directed technological change (in the sense of Acemoglu, 2002) could induce states with larger immigrant populations to slow down the speed of their skill-biased technological adoption. Perhaps by adopting efficient but less skill-intensive technologies, those states might have experienced relative faster growth in A_L . Lewis (2005) and Beaudry, et al. (2006) both show that immigration seems to slow down the adoption of skill-intensive techniques. One interesting fact is that the productivity bias in favor of less educated workers takes place together with a general, positive productivity effect. This is possibly due to efficiency gains, specialization gains or increases in effort. The idea that native workers also increase their effort in the face of competition from immigrants is also supported by the effect on hours worked shown in Table 5. All in all, in spite of some degree of variability which depends on the elasticity assumed and the method of estimation we can conclude that there is evidence in favor of a positive correlation between immigration shocks and total productivity in a state, and mild evidence that this productivity gain results more from the improving productivity of less educated workers than from improving the productivity of the better educated workers. Armed with these estimates and the theoretical relation (in 9 and 10) between

the marginal productivity of workers, factor productivity and factor supply, we can simulate the impact of the actual immigration shocks on wages at the state level and analyze how each channel (labor supply, capital adjustment and productivity changes) contributed to it.

6 Effects of Immigration on Wages, 1990-2006

6.1 Simulated Wage Effects

Table 8 shows the inflow of immigrants as a percentage increase in hours worked over the 1990-2006 period for the top and bottom five states, and provides the simulated effects, using our production-function approach, on the wages of more and less educated workers in those states. The exercise is conducted in the following way. We consider the actual hours worked of more and less educated (l and h) workers, the capital stock, and factor-specific productivity (A_L and A_H) in each state in year 1990. These values allow us, using 9 and 10 to compute the wages of more and less educated workers as of 1990. Then we consider the inflow of immigrants between 1990 and 2006. This inflow has a *direct* effect on hours worked and on the relative composition of l and h in each state. Since we estimated that there is no response of natives to immigrants in relative and absolute labor supply, the *direct* effect is the only one that we incorporate as having an effect in changing the hours worked as a consequence of immigration. Immigration, however, also had an indirect effect through the impact on capital per worker and through the impact on the productivity of factors. We obtain the percentage effect on k_{st} by multiplying the increase in hours worked due to immigrants, $\frac{N_{s2006}^F - N_{s1990}^F}{N_{s1990}}$ by $\hat{\psi}$ (estimated from regression 12) for which we choose the value reported in Table 5, Column 4 (-0.03). Similarly, we obtain the percentage changes in A_L and A_H by multiplying $\frac{N_{s2006}^F - N_{s1990}^F}{N_{s1990}}$ for each state by $\hat{\rho}_L$ and $\hat{\rho}_H$ estimated from regressions 13 and 14. For those parameters we use the average value across columns, estimated in the specifications of Table 7 that use $\sigma = 1.75$. This produces $\hat{\rho}_L = 0.60$ and $\hat{\rho}_H = 0.40$. The values of l_{s1990} , h_{s1990} , k_{s1990} , $(A_L)_{s1990}$ and $(A_H)_{s1990}$ are increased in percentage terms as described above and constitute the values that we use to calculate the corresponding variables and the wages of more and less educated workers in year 2006. We have essentially modified all factors to account only for the inflow of immigrants, using the response coefficients estimated for each factor in Sections 4 and 5. The percentage changes in wages implied by this exercise are reported in Table 8 for the top and bottom immigration states and for the U.S. Columns 1 to 3 report the measures of immigration in each state, as a percentage of initial hours worked. Column 1 shows the overall impact of immigrants on hours worked and Columns 2 and 3 the impact for the groups of more (some college plus) and less (high school and less) educated workers, respectively. First, notice that the states with large immigration inflows also tend to receive immigrants who are relatively less educated (except Florida whose inflow 1990-2006 was essentially balanced), while states with small immigration rates tend to

receive relatively more highly educated immigrants. The U.S. as a whole exhibits only a small unbalance of immigration flows toward the less educated. Second, notice that in large immigration states the combined relative supply and productivity effects produce significant positive effects on wages of more educated workers, while for less educated workers the effects are much smaller: positive in two cases, and negative in three cases. Only Arizona, the state with the largest unbalance toward less educated immigration experienced a non-trivial negative impact on the wages of less educated workers (-5.4%). In Nevada and California immigration had negligible effects on the wages of less educated workers, while in Florida it had a significantly positive effect (+3.6%). Conversely, states with small immigration flows exhibit very small effects on wages, usually positive for less educated workers. Therefore, in spite of quite large relative effects on the wages of more and less educated workers, immigration does not exhibit much of a depressing effect on the wages of the less educated workers because of the positive productivity response and the capital adjustment. The case of Nevada is telling. While receiving a massive inflow of immigrants (43% of the 1990 labor supply) over the 1990-2006 period, and in spite of the unbalanced flow favouring the less educated (although not as dramatic as the inflow in Arizona), less educated workers only experienced a -0.6% loss in wages, while more educated workers gained almost 13% of the real value of their wages. The gains in productivity, efficiency and effectiveness (in short of A_L and A_H) compensated the negative supply shock for less educated workers and added a large wage premium to highly educated workers. At the average national level both groups (more and less educated) gained in terms of real wages. While relative wages moved by 1.6% in favor of more educated workers, this happened with both groups gaining in real terms. The relative effects on wages at the average national level are in line with the simulations presented in Table 7 of Ottaviano and Peri (2008), where they assume perfect substitutability between natives and immigrants. However, in the present study we obtain an additional positive effect on average wages coming from the productivity effects of immigration that were ruled out in Ottaviano and Peri (2008).

Table 9 illustrates the importance of accounting for the capital and technology response (rather than assuming them fixed) when simulating the effect of immigration on wages. Columns 1 and 2 in Table 9 report the simulation of wage effects following the procedure described above (and are identical to Columns 4 and 5 of Table 8). Columns 3 and 4 report the effects that one would simulate assuming total capital K_{st} as constant in response to immigration (implying a corresponding decline in k_{st}) over the period 1990-2006, while still allowing for productivity responses. Under such a scenario all workers from high immigration states would experience non trivial negative wage effects and less educated workers would incur in real wage losses as large as 17% in Nevada and 14% in Arizona. This would generate a very strong negative correlation between immigration and the wages of less educated workers. As we see below, using actual wage data, no regression suggests the existence of these large negative effects for either more or less educated workers. This seems to confirm the idea that fixed capital over 16 years of immigration is a very counter-factual assumption. Finally Columns 5 and 6 of

Table 9 show the simulated effect for fixed capital and no productivity response. Even more dramatically, in this case wages of less educated workers experience losses between 7 and 23 percentage points in high immigration states. Even the highly educated lose as much as 12.6% in Nevada (in contrast with their 13% gain in the baseline simulation). These negative effects on wages are even more counter-factual and therefore the productivity increase also seems a key ingredient in understanding the effects of immigration. These experiments show how relevant it is to account for the estimated capital and productivity responses if we want to simulate the effects of immigration over the long-run.

6.2 Comparison with Estimated Wage Effects, 1980-2006

Notice that the measures of wages used in the simulations of Tables 9 and 10 are constructed from expressions of marginal labor productivity described in 9 and 10 using values of A_L , A_H , k_{st} derived from manipulations of the National Accounts data (on capital and Gross State Product). More importantly, we did not use any measure of individual wages for either group to obtain those values and results. In this section we show how the impact of immigration on simulated wages (described above) compares to the impact directly estimated on actual measures of average wages constructed from individual Census data. To construct the average wage in each education-state cell we calculate the real hourly wages of individuals (equal to annual salary and income, INCWAGE, deflated using the CPI and adjusted in its topcodes as described in Appendix A, divided by hours worked in a year) and average them for each cell using weights equal to the hours worked by the individual times her personal weight. This method includes wages of all workers in the group, 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). We call w_{st}^H and w_{st}^L the average hourly wage of more and less educated workers, respectively, in state s and year t .

Tables 10 shows the effects of immigration (measured as the percentage increase in hours worked due to immigrants 1990-2006) on the simulated percentage wage change in the same period. The wages are obtained for all states as described in section 6.1. The coefficients in the first two rows show the effect of an increase of immigrants equal to 1% of hours worked in 1990 on the percentage wage of more and less educated workers. The third row combines the wages using the composition of more and less educated workers as of 1990 in order to find the effect on the average wage with the 1990 composition (to avoid mixing effects due to changes in skill composition). The three columns differ since the simulated wages use values of A_L , A_H based on different values of σ . Focussing on the estimates obtained when we use the median σ ($=1.75$) to construct wages, this regression, run on simulated data, shows that immigration had a very small (negative) and non-significant effect on less educated wages and a positive, significant effect close to 0.30 on wages of more educated workers. Also, in all specifications, the average wage effect is positive and very significant and in the median case the elasticity

of average wages to immigration is equal to 0.16. The simulated wages, constructed from national account data, therefore imply that an increase in labor supply by 10% due to immigrant has no effect (possibly a -0.4% effect) on the wages of less educated workers while it increases by a significant 3% the wages of more educated workers and by 1.6% the average wages.

Table 11 shows the estimates using the Census measures of hours worked and average wages by state and year. To keep the samples close to the period of the simulation we use Census data from 1980, 1990, 2000 and 2006 and we estimate a panel with the dependent variable being either the percentage change of average wages of more educated workers (first row of table 11) or the percentage change of wages of less educated workers (second row). The last row combines the two estimated changes in order to evaluate the estimated average wage change for the skill-composition as of 1990. We always include decade fixed effects and we cluster the standard errors at the state level. The differences between the estimates reported in different columns are the estimation methods. In Column 1 we show the coefficients estimated using weighted least squares, in Column 2 we show those estimated using 2SLS with only geographic instruments (interacted with decade dummies) and in Column 3 we use geographic instruments and imputed immigrants as instruments. The 2SLS estimates of the wage effect of immigrants are somewhat smaller than the WLS ones, confirming one more time that the instruments do correct for a likely demand-driven upward bias. The estimated elasticity of the wages of less educated workers to immigrants is an insignificant -0.06/-0.07, while the elasticity of highly educated workers' wages to immigration is a strongly significant 0.42/0.44. The similarity with the estimates obtained using simulated wages is remarkable. The Census data, obtained by aggregating individual wages confirm the result from the previous literature (Card 2001, Card 2007) that immigration has a very small effect (if any) on the wages of less educated workers in the state and a significantly positive impact on the wages of more educated workers. Those effects are quantitatively very similar to those obtained using simulated wage data constructed from a theoretical production function and data on Gross State Product, physical capital and hours worked.

7 Conclusions

This paper provides some important and new empirical facts that future theories of immigration and its impact on wages and output should account for. First, it moves away from the exclusive use of individual wage data and uses national accounts data on state output, physical capital and hours worked in relation to immigration. Second, using a simple production function approach produces simple "accounting" of the impact of immigrants on factors and productivity. The paper confirms that immigration shifts the labor supply unevenly across U.S. states. An important part of that unevenness is independent of demand factors but, instead, depends on push from countries of origin and the geographical location of U.S. states relative to initial immigrant communities or ports of entry of new communities. Moreover, immigration shifts the relative labor supply, increasing the

share of less educated workers. This paper shows that the data do not find evidence of a response by native employment that offsets those shocks, neither in aggregate employment nor in relative employment (of more and less educated workers). However, capital and productivity seem to respond significantly to immigration. Confirming the idea that capital mobility may substitute for labor mobility, physical capital in the states adjust to maintain capital per worker essentially unchanged, even over a single decade. This diffuses any effect of decreased capital intensity on wages. At the same time, the productivity of both more and less educated workers increases significantly in association with immigrant inflows, with weak evidence that the increase may be larger for the productivity of less educated workers. The reasons for the small response in native labor supply, and for the significant response of physical capital and productivity, deserves more careful research. Increased investment opportunities linked to the supply of immigrant labor and skills, gains in efficiency from competition with immigrants, efficiency gains from labor division, and task specialization as well as the adoption of appropriate and efficient technologies have all been shown to be plausible effects of immigration. The simple empirical decomposition analyzed in this paper allows us to show that the simultaneous, positive productivity effects and capital attraction, on one side, and the adverse relative supply effect on the other, compensate each other in leading to very small wage effects for less educated workers. At the same time the capital attraction, supply effect, and productivity effect reinforce each other in leading to a significant, positive impact on the wages of more educated workers. Finally, the prompt capital response and the overall productivity effect explain the positive effects on average wages in states receiving large inflows of immigrants that persist once we correct for demand bias using geographic factors to predict immigration.

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A Appendix: Census Data on Worked Hours and Wages

We downloaded the IPUMS data on April 10th 2008,. The data are relative to these samples:

1960 1% sample of the census; 1970 1% sample of the census; 1980 1% sample of the census; 1990 1% sample of the census; 2000 1% sample of the census; 2006 1% sample of the ACS

We constructed a datasets that cover all employed workers in the U.S. and calculates their average wages and hours worked by state and year.

A.1 Definition of the Samples

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 17. Since people of working age are defined by BLS as those 16 and older, and since the questions related to work variables pertain to the previous year, we consider 17 years of age as the cut-off.

3) Eliminate those who worked 0 weeks last year, which corresponds to wkwork2=0 in 1960 and 1970 and wkwork1=0 in 1980-1990-2000 and ACS.

4) Once we calculate experience as age-(time first worked), where (time first worked) is 16 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.

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

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

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.

Construction of the average hourly wage by cell

In each cell we average the hourly 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.

A.2 Individual Variables Definition and Description

Education: Education 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 less educated

(L) those with EDUCREC \leq 7, corresponding to high school degree or less. Highly educated are those with EDUCREC \geq 8 corresponding to some college or ore.

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 workers with no degree, 19 years for high school graduates, 21 years for those with some college education and 23 years for college graduates.

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:

<i>Year</i>	1959	1969	1979	1989	1999	2005
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<i>Deflator</i>	5.725	4.540	2.314	1.344	1.000	0.853
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Topcodes for Yearly Wages: Following an established procedure we multiply the topcodes for yearly wages in 1960, 1970 and 1980 by 1.5.

Hourly Wages: The hourly wage for an individual is constructed by dividing the yearly wage as defined

above by the number of weeks worked in a year times the number of hours worked in a week.

B Appendix: Construction of the Immigration Instruments

The imputed growth of immigrants as a share of the working age population was calculated as follows: We first identify from the Census foreign-born workers (using the variable BPLD for 1960 and CITIZEN for 1970 and later) from 10 different areas: Mexico, Rest of Latin America, Canada-Australia-New Zealand, Western Europe, Eastern Europe and Russia, China, India, Rest of Asia, Africa and Others. Let us call those ten the "nationality of origin" of the immigrants. For each nationality of origin n and each state i the total number of people in working age (16-65) in Census 1960 can be called $Pop_{n,i,1960}$. For each nationality of origin we also calculate the rate of growth of the total working age population in the U.S., namely: $g_{n,1960-t} = (Pop_{n,t} - Pop_{n,1960})/Pop_{n,i,1960}$. This allows us to impute the immigrant population from each nationality of origin in each state, by applying the national growth rate to the 1960 population from that nationality, to each state. Hence the "imputed" immigrant population from nationality n in state i would be $\widehat{Pop}_{n,i,t} = Pop_{n,i,1960} * (1 + g_{n,1960-t})$. Adding across nationalities we have the total imputed population of immigrants in each state and year: $\widehat{Pop}_{Fi,t} = \sum_n \widehat{Pop}_{n,i,t}$. Finally, we construct the imputed decennial growth of working age population due to immigration as $(\widehat{Pop}_{Fi,t+10} - \widehat{Pop}_{Fi,t}) / (\widehat{Pop}_{Fi,t} + Pop_{U.S.,i,t})$ where $Pop_{U.S.,i,t}$ is the actual native population of working age in state i and year t . We use this measure as an instrument for the growth in hours worked due to immigrants in each state and decade.

The US-Mexico border (for Mexican immigrants) and Los Angeles, New York and Miami (for other travellers) are the main points of entry to the U.S. The distance of each state's center of gravity from the Border, New York, Los Angeles and Miami is calculated as follows. First, we obtain data on the geodesic coordinates of each state's population center of gravity from the 2000 Census as well as for 12 sections of the U.S.- Mexican border covering its whole length and for New York, Los Angeles and Miami. We then use the formula for geodesic distance to calculate the distance (in thousands of kilometers) between each state's center of gravity and the relevant points of entry. Since we already control for state fixed effects in the regressions, we interact the logarithmic distance variables with five decade dummies (60's, 70's, 80's, 90's and 00-06). This captures the fact that distance from the border had a larger effect in predicting the inflow of immigrants in decades with larger Mexican immigration and the distance from L.A. had larger impact on immigrants inflow in periods of large immigration from China and Asia.

C Appendix: Construction of Physical Capital by State

In our construction of the state capital stocks we follow Garafalo and Yamarik (2002). This involved distributing the national capital stock by industry and year, obtained from the BEA (2008b), to each state and industry and year according to the percentage of value added for the state and industry and year in the national value added for that industry and year, obtained from the BEA (2008a). In other words, following the notation of the paper and denoting as j one industry, we constructed capital stocks for state s and industry j as :

$$K_{s,j}(t) = \left[\frac{Y_{s,j}(t)}{Y_j(t)} \right] K_j(t)$$

We then summed over all industries j , for each state s , in year t , to obtain a capital stock series by state and year. Finally, we used as price deflator the implicit capital deflator, obtained from the aggregate BEA data to transform the capital stock series into real values. Furthermore, the value added data at the state level needed to be generated for all years using a concordance, as described below. That concordance left us with 19 industries that we use to attribute capital stock. The industries are: Agriculture; Forestry; Fishing and Hunting; Mining; Utilities; Construction; Manufacturing; Wholesale Trade; Retail Trade; Transportation and Warehousing; Information, Finance and Insurance; Real Estate and Rental and Leasing; Professional, Scientific, and Technical Services; Management of Companies and Enterprises; Administrative and Waste Management Services; Educational Services; Health Care and Social Assistance; Arts, Entertainment, and Recreation; Accommodation and Food Services; Other Services, except Government.

Constructing the NAICS97 to SIC87 Concordance

The first step in generating the capital stock by state was to generate a crosswalk, or concordance, from NAICS97 to SIC87 using the Census Bureau's crosswalks at <http://www.census.gov/epcd/ec97brdg/index.html>. This step was necessary in order to extend the BEA's value added by state data to pre-1997 dates. The bridge from naics97 to sic87 (NtoS) lists a naics code and then the corresponding sic codes that go into it, and then the establishments, sales, payroll and employees per that combination. The file does not, however, list the percentage of the sic category which should be attributed to the naics code, and since there may be more than one naics code per sic code, this information is needed. The HTML version on the website does list this percentage, but it is unfortunately not in the electronic file. This percentage can be calculated using the opposite bridge from sic87 to naics97 (StoN). The StoN file contains the same variables as the NtoS file, but maps all the naics that go into a given sic. Also available are the totals of the 4 categories (sales, etc.) for each sic code, at different digit levels (2-digit, 3-digit, etc.).

We delete everything in the StoN file except the sic totals (we delete the sic to naics mappings). We then merge these to the NtoS file by sic code, so that now the NtoS file has the mapping as before, but also includes

the totals for each sic value next to each naics-sic pair. Then the percentage can be calculated for each naics-sic combination by dividing the naics-sic totals into the merged sic totals. Since what we actually want is sic2 to naics2, and the original mapping (NtoS) is actually sic4 to naics6, before merging the sic4 totals into the NtoS file we trimmed the naics codes down to 2 digits, and then summed up over the unique sic4-naics2 combinations. We then trimmed the sic4 values to sic2, and summed over the unique sic2-naics2 values. Finally, we merged in the sic2 totals from the StoN file and calculated the percentage of each sic2 that goes into each naics2.

Tables and Figures

Table 1: Immigration and Total Hours Worked: 1960-2006

Dependent Variable: decennial change of total hours worked (as % of initial hours)	(1) WLS, 1960- 2006	(2) WLS, 1970-2006	(3) IV: Geo Instruments	(4) IV: Imputed Immigrants and Geo Instruments	(5) Including lagged change in total hours.
Decennial Change in immigrant labor supply (as % of initial supply)	1.68*** (0.48)	1.64*** (0.48)	1.18*** (0.48)	0.96*** (0.32)	0.87*** (0.39)
Observations	255	204	255	255	
Decade fixed effects	Yes	Yes	Yes	Yes	Yes
First stage: F-test of joint significance of IV					
Geo Instruments	n.a.	n.a.	29.8		29.8
Imputed Immigrants	n.a.	n.a.		44.6	

Note: Each cell in the first row reports the estimated coefficient of a regression of the change in total worked hours on the change of worked hours by immigrants, both as a percentage of initial total hours worked. Specifications 1-2 use weighted least squares as the method of estimation. The weights are equal to the employment in each cell. Specifications 3-5 use 2SLS. The Geographic Instruments are the distance from the border, the distance from New York and the distance from Los Angeles (largest port of entry for international travelers) interacted with decade dummies. The “Imputed Immigrants” instrument is constructed using the initial distribution of immigrants from 10 places of origin in 1960 and imputing to each group in each state the national percentage growth. The entries in the last two rows report, where applicable, the value of an F-test of joint significance of the instruments. The units of observations are 50 states plus DC for 1960, 1970, 1980, 1990, 2000 and 2006. We report heteroskedasticity-robust standard errors, clustered by state.

***, **, *=Significant at 1%, 5% and 10% level.

Table 2: Immigration and Hours Worked by Natives: 1960-2006

Dependent Variable: decennial change of hours worked by natives (as % of initial hours)	(1) WLS, 1960- 2006	(2) WLS, 1970- 2006	(3) IV: Geo Instruments	(4) IV: Imputed Immigrants and Geo Instruments
Decennial Change in immigrant labor supply (as % of initial supply)	0.92* (0.50)	0.87 (0.50)	0.38 (0.49)	0.16 (0.33)
Observations	255	204	255	255
Time Fixed Effects	Yes	Yes	Yes	Yes
First stage: F-test of joint significance of IV				
Geo Instruments	n.a.	n.a.	29.8	44.6
Imputed Immigrants	n.a.	n.a.		

Note: Each cell in the first row reports the estimated coefficient of a regression of the change in hours worked by natives as a percentage of initial total hours on the change in worked hours by immigrants as a percentage of initial total hours. The rest is as in specifications 1-4 of Table 1.

***, **, *=Significant at 1%, 5% and 10% level.

Table 3: Immigration and Relative Supply of Less Educated Workers: 1960-2006**Less Educated=High school degree or less**

Dependent Variable: Change in share of total hours worked by less educated	(1) WLS, 1960- 2006	(2) WLS, 1970- 2006	(3) IV: Geo Instruments	(4) IV: Imputed Immigrants and Geo Instruments
Decennial Change in immigrant labor supply (as % of initial supply)	0.17*** (0.03)	0.19*** (0.04)	0.25*** (0.04)	0.24*** (0.03)
Observations	255	204	255	255
Time Fixed Effects	Yes	Yes	Yes	Yes
First stage: F-test of joint significance of IV				
Geo Instruments	n.a.	n.a.	29.8	44.6
Imputed Immigrants	n.a.	n.a.		

Note: Each cell in the first row reports the coefficient of a regression of the change in the share of hours worked by workers with a high school degree or less on the change in hours worked by immigrants as a percentage of total initial hours worked. Specifications and Instruments are as in column 1 to 4 of Table 1. We report the Heteroskedasticity-robust standard errors, clustered by state. ***, **, *=Significant at 1%, 5% and 10% level.

Table 4: Immigration and Relative Supply of Native, Less Educated Workers: 1960-2006**Less Educated=High school degree or less**

Dependent Variable: Change in share of hours worked by less educated among natives	(1) WLS, 1960- 2006	(2) WLS, 1970-2006	(3) IV: Geo Instruments	(4) IV: Imputed Immigrants and Geo Instruments
Decennial Change in immigrant labor supply (as % of initial supply)	0.01 (0.02)	0.03 (0.02)	0.04 (0.04)	0.06 (0.035)
Observations	255	204	255	255
Time Fixed Effects	Yes	Yes	Yes	Yes
First stage: F-test of joint significance of IV:				
Geo Instruments	n.a.	n.a.	29.8	44.6
Imputed Immigrants	n.a.	n.a.		

Note: Each cell in the first row reports the coefficient of a regression of the change in the share of hours worked by those with a high school degree or less among native workers on the change in worked hours by immigrants as a percentage of initial total hours. Specifications and Instruments are as Column 1 to 4 in Table 1. We report the Heteroskedasticity-robust standard errors, clustered by state. ***, **, *=Significant at 1%, 5% and 10% level.

**Table 5: Immigration and GSP per worker: 1960-2006
Decomposed: Hours per worker and GSP per hour**

Explanatory variable: Decennial Change in immigrant labor supply (as % of initial supply)	(1) WLS	(2) IV: Geo Instruments	(3) IV: Imputed Immigrants and Geo Instruments	(4) IV: Geo Instruments Controlling for Initial Value	(5) IV: Imputed Immigrants and Geo Instruments Controlling for Initial Value
Dependent variable:					
Change in GSP per worker	0.67*** (0.21)	0.36*** (0.16)	0.47*** (0.20)	0.48*** (0.12)	0.78*** (0.25)
Change in hours per worker	0.11*** (0.01)	0.09*** (0.02)	0.10*** (0.02)	0.01 (0.02)	0.02 (0.03)
Change in GSP per hour	0.54*** (0.20)	0.27* (0.15)	0.37* (0.18)	0.42*** (0.12)	0.69*** (0.23)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	255	255	255	255	255

Note: Each cell in the first three rows report the coefficient from a different regression. In the first row we regress the percentage change in gross state product per person on the change in immigrant labor. In the second row the dependent variable is change in hours worked per person. In the third row it is change in GSP per hour worked. The units of observations are 50 states plus DC for 1960, 1970, 1980, 1990, 2000 and 2006. Each regression includes time fixed effects. Specifications (4) and (5) include the lagged value of GSP per worker (first row), hours per worker (second row) and GSP per hour (third row). We report heteroskedasticity-robust standard errors, clustered by state.

***, **, *=Significant at 1%, 5% and 10% level.

Table 6: Immigration and Capital per worker; 1960-2006

Dependent Variable: Decennial Change in immigrant labor supply (as % of initial supply)	(1) WLS 1960-2006	(2) WLS 1970-2006	(3) IV: Geo Instruments	(4) IV: Imputed Immigrants and Geo Instruments
Change in capital per worker (in % of initial value)	-0.21 (0.35)	-0.16 (0.31)	-0.01 (0.30)	-0.03 (0.28)
Time Fixed effects	Yes	Yes	Yes	Yes
Initial capital stock	Yes	Yes	Yes	Yes
Observations	255	204	255	255

Note: Each cell in the first row report the coefficient from a different regression. We regress the net percentage change in physical capital (in the state) per person on change in immigrant labor, measured as usual as increase in hours worked. The units of observations are 50 states plus DC for 1960, 1970, 1980, 1990, 2000 and 2006. Each regression includes time fixed effects and the initial value of the log of physical capital in the state. We report heteroskedasticity-robust standard errors, clustered by state.

***, **, *=Significant at 1%, 5% and 10% level.

Table 7: Immigration and Productivity of More and Less Educated Workers: 1960-2006

(1) Sigma	(2) Explanatory variable: Decennial Change in immigrant labor supply (as % of initial supply)	(3) WLS, 1960-2006	(4) IV: Imputed Immigrants	(5) IV: Imputed Immigrants and Geo Instruments
$\sigma=1.5$ low	Change in A_H	-0.13 (0.43)	-0.80** (0.30)	-0.05 (0.58)
	Change in A_L	0.50*** (0.30)	0.32*** (0.21)	1.03*** (0.26)
	Change in $(A_H + A_L)^{1-\alpha}$	1.03*** (0.20)	0.92*** (0.20)	1.02*** (0.34)
$\sigma=1.75$ typical	Change in A_H	0.48 (0.35)	0.04 (0.25)	0.67** (0.53)
	Change in A_L	0.53* (0.31)	0.32 (0.20)	0.97** (0.26)
	Change in $(A_H + A_L)^{1-\alpha}$	0.79*** (0.19)	0.65** (0.16)	1.02*** (0.29)
$\sigma=2$ High	Change in A_H	0.72*** (0.32)	0.37 (0.24)	0.97* (0.50)
	Change in A_L	0.56** (0.31)	0.33 (0.20)	0.95 (0.28)
	Change in $(A_H + A_L)^{1-\alpha}$	0.70*** (0.19)	0.56** (0.16)	0.95** (0.28)
	Observations	255	255	255
	Common time-effects	yes	yes	yes

Note: Each cell reports the coefficient from a different regression. Column (2) specifies the dependent variable, that is the change in L-specific, H-specific or combined productivity. A_L and A_H are computed from data on GSP per workers, capital per worker, hours worked and the relative wage share of high and less educated workers. Their value depends on the assumed parameter σ that captures the elasticity of substitution between more and less educated workers (H and L). In the first three rows A_L and A_H are calculated under the assumption that $\sigma=1.5$. In the following three we assume $\sigma =1.75$ and in the last three we assume $\sigma =2$. Each regression includes year fixed effects. In column (3) we use weighted least squares as method of estimation, and in columns (2) and (3) we use 2SLS with the usual instruments. We report heteroskedasticity-robust standard errors, clustered by state.

***, **, *=Significant at 1%, 5% and 10% level.

Table 8
Simulated Effects of Immigration, 1990-2006, on Wages:
Combining the Effects on Capital, Productivity and Labor Supply

State	(1) Immigrants 1990-2006 as % of initial hours worked	(2) Highly Educated Immigrants 1990-2006 as % of group	(3) Less Educated Immigrants 1990-2006 as % of group	(4) Simulated % change in w_L due to immigrants ,	(5) Simulated % change in w_H due to immigrants
Nevada	43.0%	28.4%	60.5%	-0.6%	12.9%
Arizona	25.3%	13.6%	44.3%	-5.4%	8.5%
Florida	21.1%	21.3%	21.0%	3.6%	3.5%
Texas	19.5%	12.4%	29.2%	-2.2%	5.9%
California	19.0%	15.7%	24.5%	0.0%	4.3%
Aggregate U.S.	11.5%	10.1%	13.9%	0.6%	2.2%
North Dakota	3.5%	4.7%	1.4%	1.9%	0.1%
Maine	1.6%	2.8%	0.3%	1.1%	-0.3%
Vermont	1.4%	2.9%	-0.5%	1.5%	-0.5%
West Virginia	1.2%	2.3%	0.4%	0.7%	-0.4%
Montana	0.2%	0.1%	0.2%	0.0%	0.0%

Note $\sigma=1.75$, $\alpha=0.33$. Wages in 1990 are calculated using the formulas (9) and (10) in the main text and the actual values of k , A_L , A_H , l and h as of 1990. Then the values are augmented by the predicted response of each variable to immigration 1990-2006: in the case of h and l we directly measure how immigration affects them and in the case of the other variables we use the estimated elasticity. Wages in 2006 are then calculated using the formulas (9) and (10) and the augmented variable values.

Table 9
Counterfactual Simulated Scenarios

Scenario	Simulated Changes		Simulated Changes with no Capital Response		Simulated Changes with no Capital and no Technology Response	
State	(1) $\Delta W_L/W_L$	(2) $\Delta W_H/W_H$	(3) $\Delta W_L/W_L$	(4) $\Delta W_H/W_H$	(5) $\Delta W_L/W_L$	(6) $\Delta W_H/W_H$
Nevada	-0.6%	12.9%	-17.1%	-5.9%	-23.1%	-12.6%
Arizona	-5.4%	8.5%	-13.9%	-1.2%	-17.5%	-5.4%
Florida	3.6%	3.5%	-4.0%	-4.1%	-7.4%	-7.6%
Texas	-2.2%	5.9%	-8.8%	-1.2%	-11.8%	-4.5%
California	0.0%	4.3%	-6.5%	-2.5%	-9.5%	-5.6%
Aggregate U.S.	0.6%	2.2%	-2.7%	-1.1%	-4.1%	-2.6%
North Dakota	1.9%	0.1%	0.8%	-1.1%	0.2%	-1.7%
Maine	1.1%	-0.3%	0.6%	-0.8%	0.3%	-1.1%
Vermont	1.5%	-0.5%	1.0%	-0.9%	0.8%	-1.1%
West Virginia	0.7%	-0.4%	0.3%	-0.8%	0.1%	-1.0%
Montana	0.0%	0.0%	-0.1%	0.0%	-0.1%	0.0%

Note $\sigma=1.75$, $\alpha=0.33$. Simulations in the first two columns reproduce those in table 8, last columns. Simulations in Column 3 and 4 impose no change in capital so that the capital-labor ratio decreases in percentage points by the whole percentage increase of employment due to immigration. The last two columns also impose zero response of A_L and A_H to immigration.

Table 10
Regression Coefficients on the Simulated Data: Cross-Section of 1990-2006 Change

Explanatory variable: Decennial Change in immigrant labor supply (as % of initial supply)	$\sigma=2.00$	$\sigma=1.75$	$\sigma=1.5$
Change in Average wage of Highly educated	0.31*** (0.03)	0.27*** (0.03)	0.17*** (0.03)
Change in Average wage of Less Educated	0.04 (0.05)	-0.04 (0.05)	-0.16*** (0.08)
Change in Average wage at fixed, 1990, h and l	0.21** (0.01)	0.16** (0.01)	0.054** (0.01)
Number of Observations	51	51	51

Note: we calculate the wages of highly and less educated workers using the formulas in the text that predict the marginal productivity of each type of worker as a function of A_L , A_H , k , l and h in 1990. Then we consider the actual inflow of immigrants 1990-2006 and how it directly changes l and h and we simulate how it affects indirectly k , A_L , A_H using the estimated response of these variables to immigration. Then we calculate wages in 2006 according to the formulas and we obtain their percentage change. This constructed change in wages is regressed on the change in immigrants as % of initial worked hours.

Table 11
Immigration and Wages, Estimated Coefficients 1980-2006

Explanatory variable: Decennial Change in immigrant labor supply (as % of initial supply)	OLS, 1980-2006	IV: Geo Instruments	IV: Imputed Immigrants and Geo Instruments
Change in Average wage, more educated (w_h)	0.50*** (0.08)	0.44*** (0.07)	0.42*** (0.07)
Change in Average wage, less educated (w_l)	0.09 (0.08)	-0.06 (0.06)	-0.07 (0.07)
Change in Average wage at fixed, 1990, h and l	0.35*** (0.07)	0.26*** (0.06)	0.26*** (0.06)
Number of Observations	153	153	153

Note: The average wages in the education group in a state-year are constructed weighting individual hourly wages by their hours worked. In the first row we report the estimated correlation between immigration (in percentage of initial hours worked) and the change in wages of more educated workers. In the second row we report the estimated effect on wages of less educated workers. In the third row we combine the effects for given composition of more and less educated workers (as of 1990). Observations are changes in 1980-90, 1990-2000 and 2000-06 for 50 us-states plus D.C.

Figures

Figure 1
Top and Bottom Immigration States, 1960-2006

Cumulated immigrant Labor Supply across states, 1960-2006

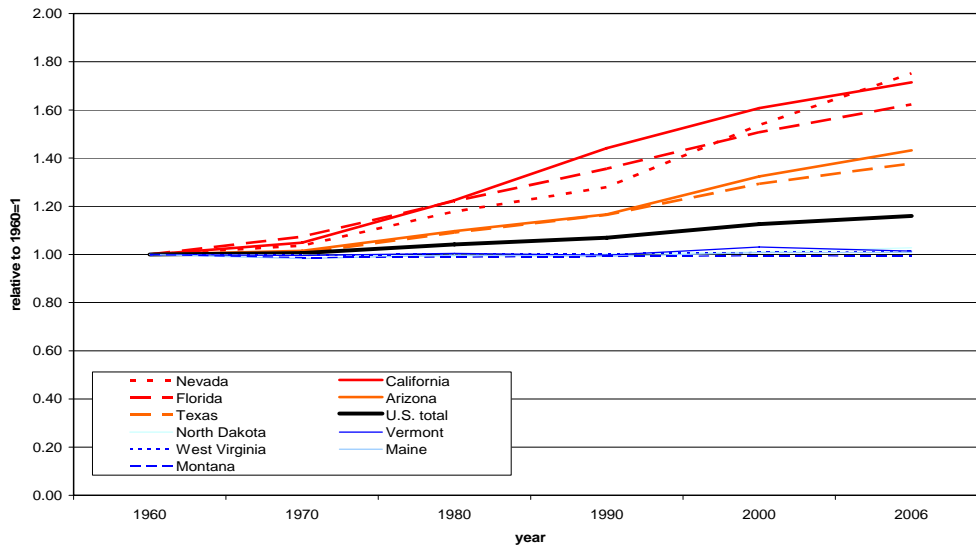


Figure 2
Employment Growth in Top and Bottom Immigration States 1960-2006

Employment in Hours across states, 1960-2006

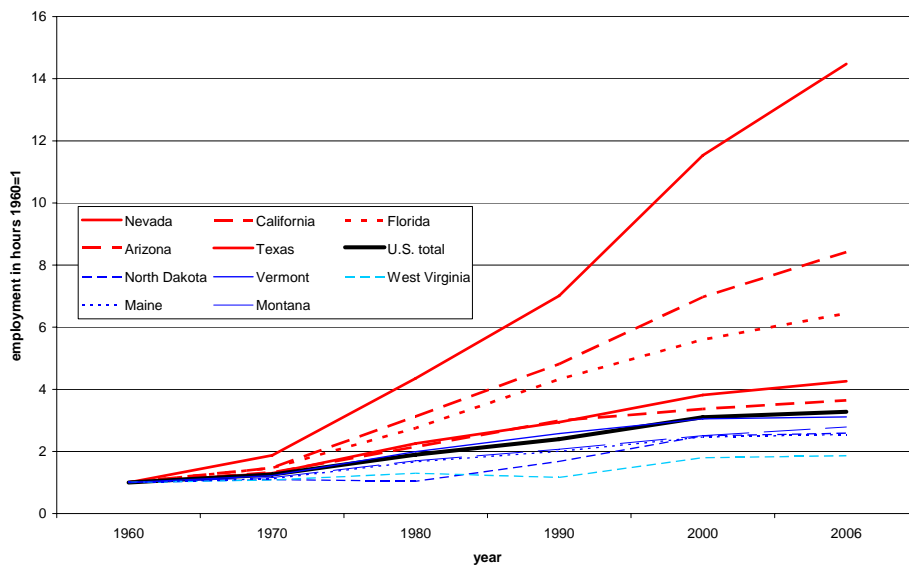
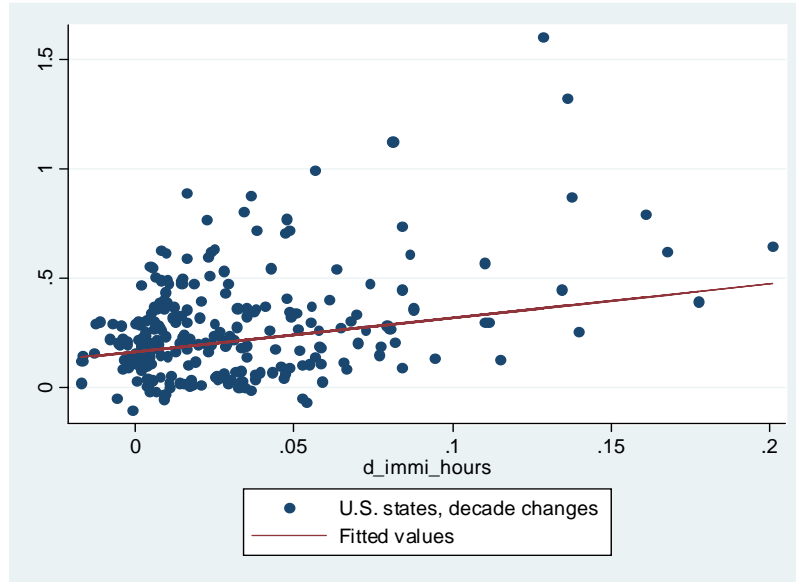


Figure 3
 Correlation between change in immigrants' labor supply and change in total labor supply
 U.S. States, decennial changes, 1960-2006



Note: slope=1.55 standard error=0.26

Figure 4
 Share of less educated workers (HS or Less)
 Immigrants and Natives, 2006

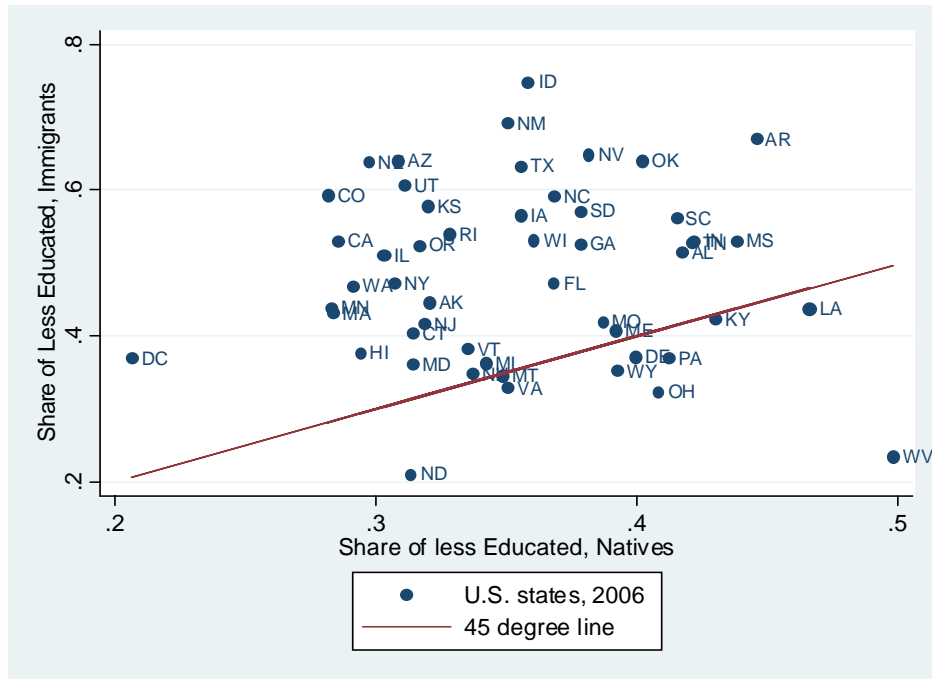


Figure 5
Cumulated change in shares of less educated workers: top and bottom immigration states

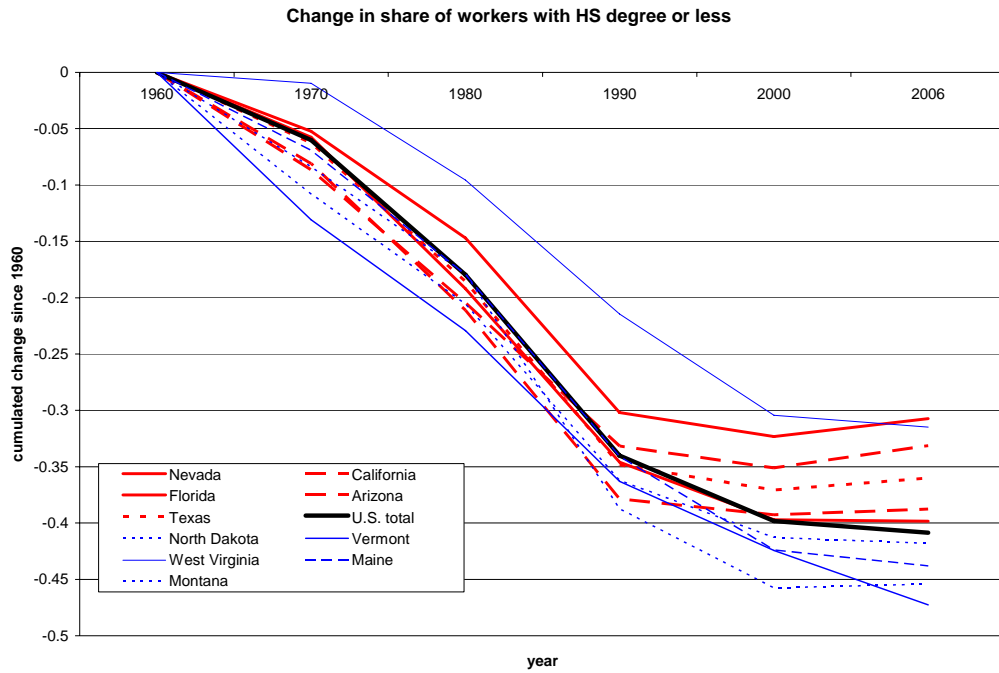


Figure 6
Cumulated changes in shares of less educated natives: top and bottom immigration states

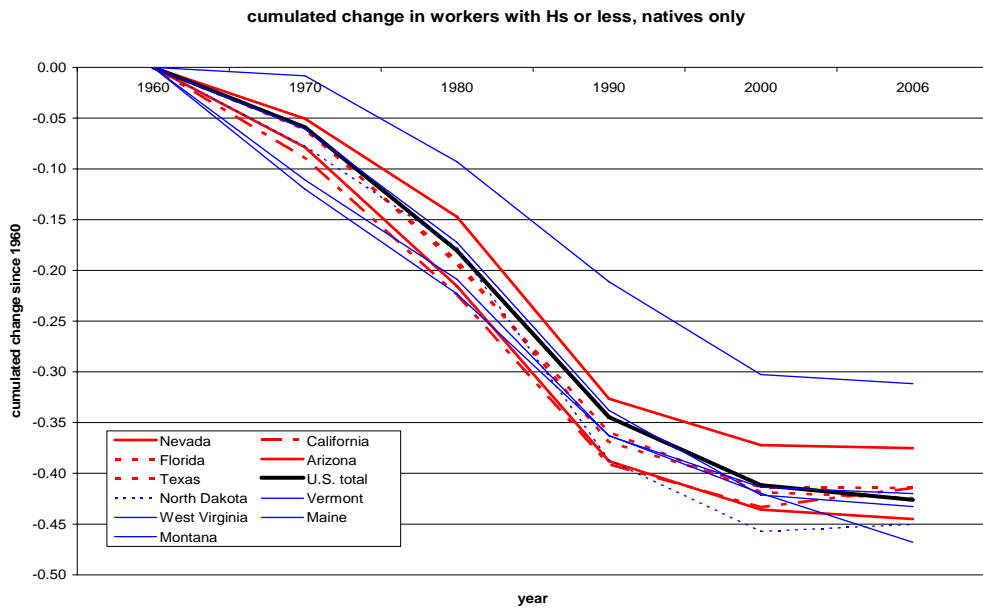
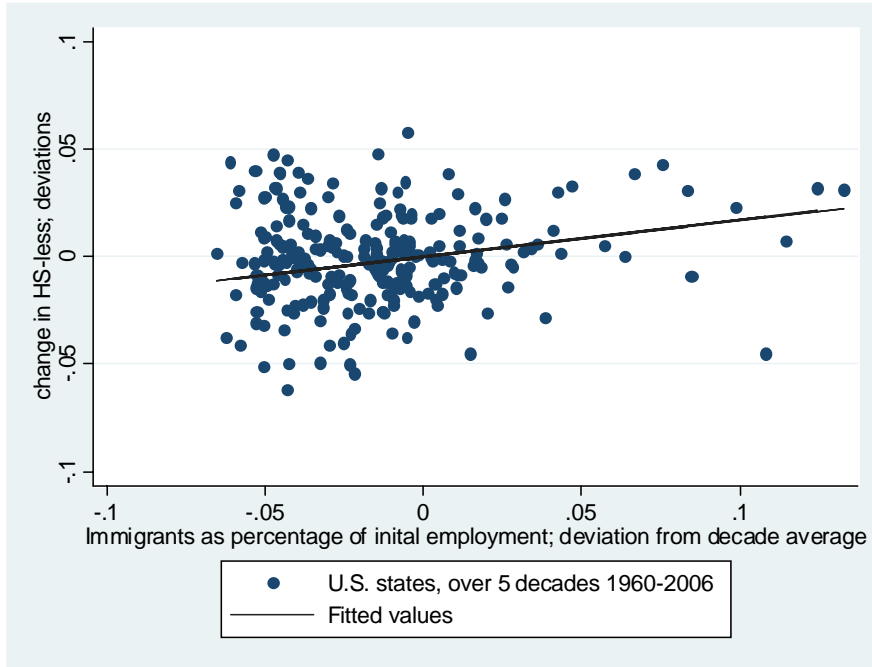
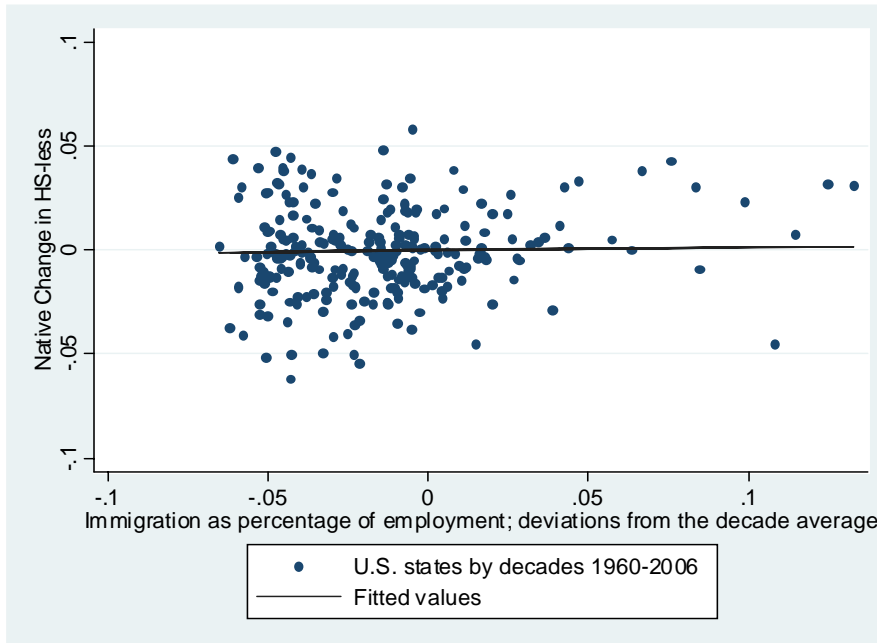


Figure 7
Correlation between change in immigrants labor supply and change in less educated workers
 U.S. States, decennial changes, 1960-2006



Note: slope=0.17 standard error=0.03

Figure 8
Correlation between change in immigrants labor supply and change in less educated native workers
 U.S. States, decennial changes, 1960-2006



Note: slope=0.01 standard error=0.03

Figure 9
Real GSP per worker in logarithmic scale
 U.S. states, 1960-2006

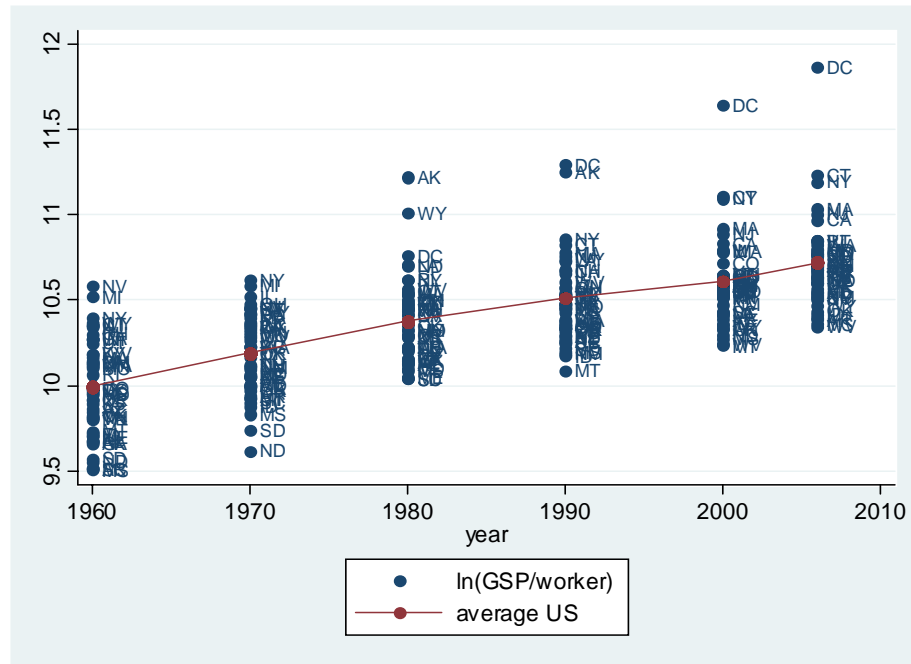


Figure 10
Real Capital per worker in logarithmic scale
 U.S. states, 1960-2006

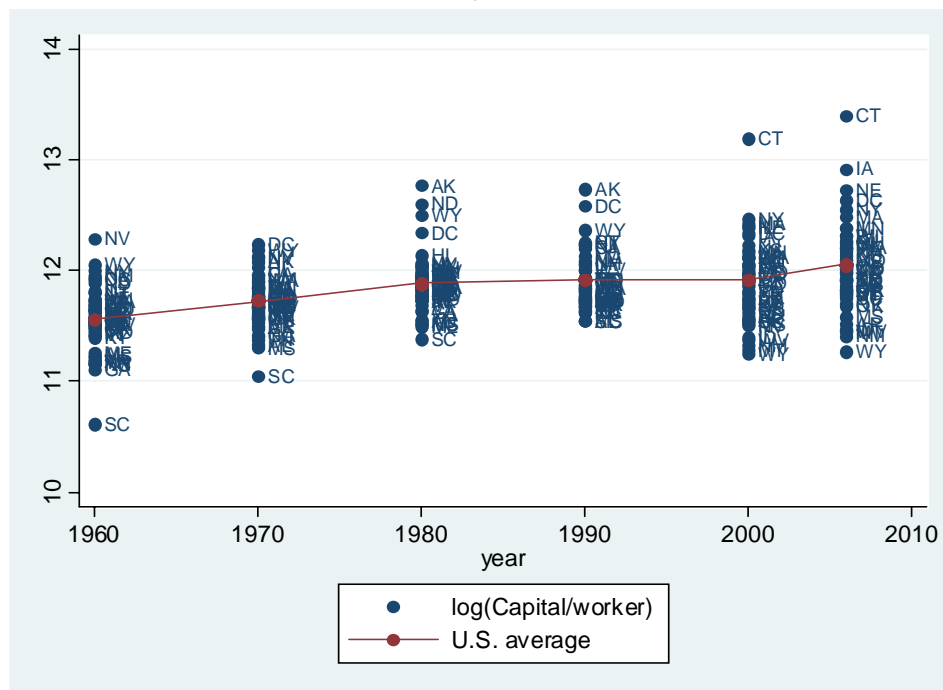


Figure 11
Productivity of highly educated workers when sigma=1.75
 U.S. states, 1960-2006

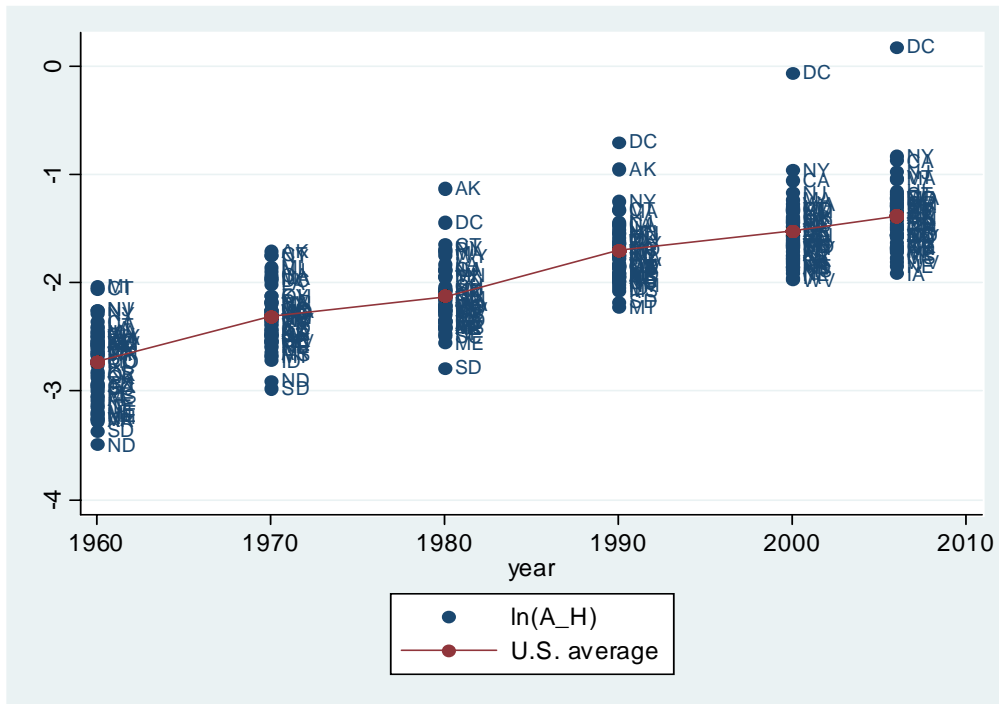
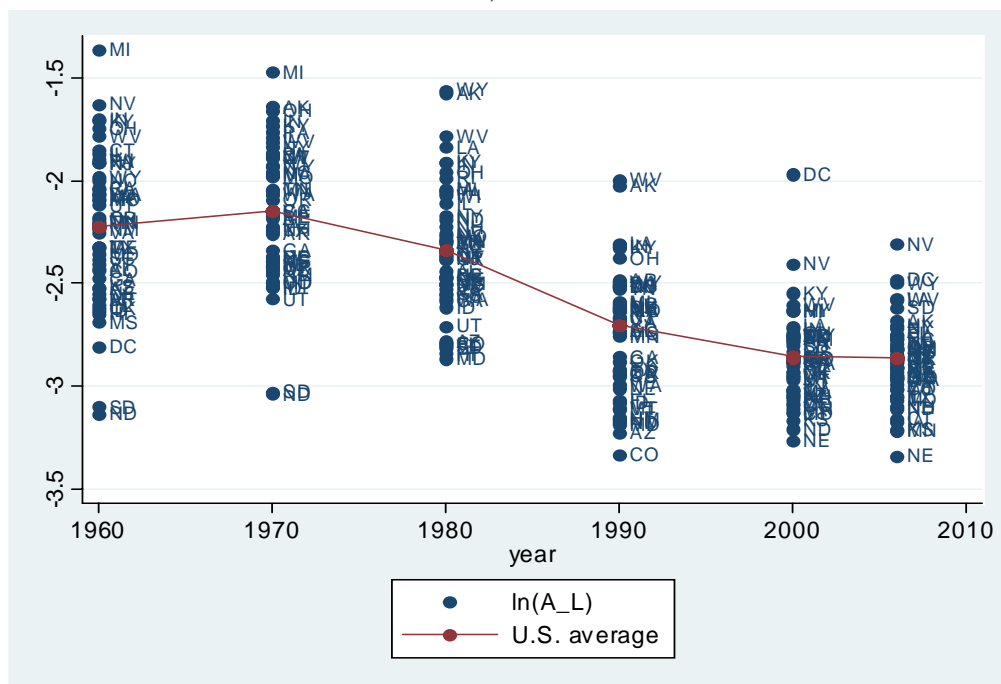
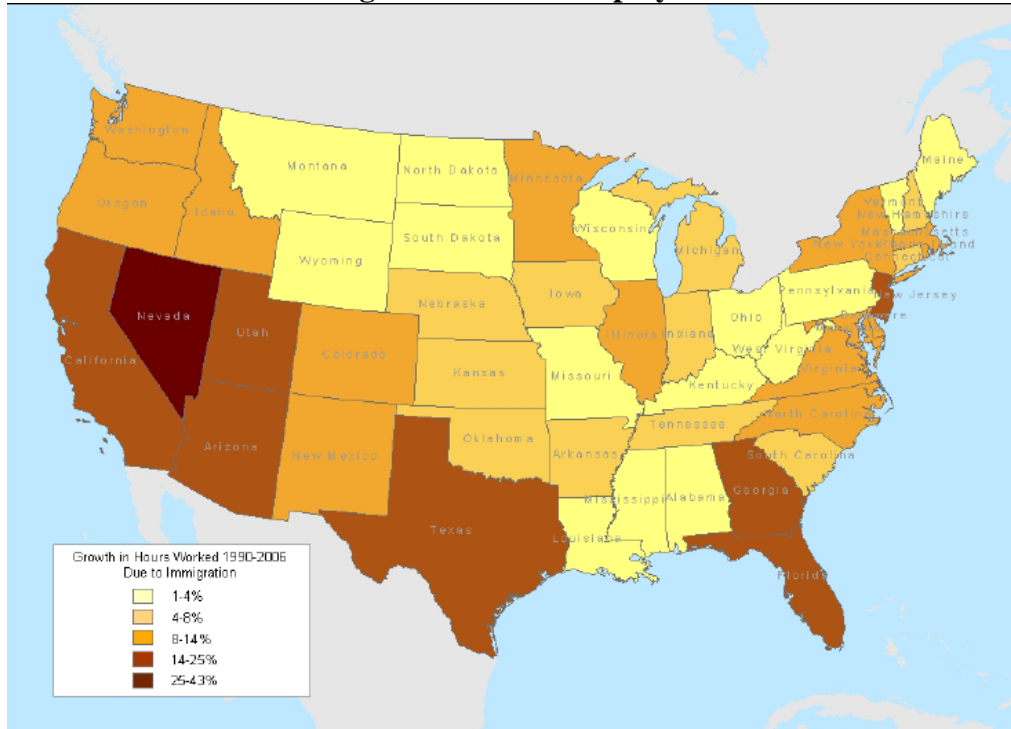


Figure 12
Productivity of less educated workers when sigma=1.75
 U.S. states, 1960-2006



Map 1
Growth of Immigrants as % of Employment 1990-2006



Map 2
Immigrants as % of Employment, U.S. States 2006

