

The Effect of Immigration on Productivity: Evidence from US States

Giovanni Peri (UC Davis and NBER)*

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Abstract

In this paper we analyze the long-run impact of immigration on employment, productivity and its skill bias. We use the existence of immigrant communities across US states before 1960 and the distance from the Mexican border as instruments for immigration flows. We find no evidence that immigrants crowded-out employment. At the same time we find that immigration had a strong positive association with total factor productivity and a negative association with the high skill-bias of production technologies. The results are consistent with the idea that immigrants promoted efficient task specialization, thus increasing TFP and they also promoted the adoption of unskilled-efficient technologies.

Key words: Immigration, Employment, Total Factor Productivity, Skill-biased Productivity.

JEL Codes: F22, J61, R11.

*Department of Economics UC Davis, One Shields Avenue, Davis CA 95616. email: gperi@ucdavis.edu. I thank Gregory Wright and Will Ambrosini for outstanding Research Assistance. I thank the editor in charge and two anonymous referees for very helpful comments on previous drafts of this paper. Participants to several seminars provided useful suggestions.

1 Introduction

Immigration during the 1990's and the 2000's has significantly increased the presence of foreign-born workers in the U.S. This increase has been very large on average and very unequal across states. Several studies have analyzed how such differential inflows of immigrants have affected different aspects of state economies such as labor markets (recently Borjas 2006, Card 2001, 2007, 2009, Peri and Sparber 2009), industrial specialization (Card and Lewis 2007) and innovative capacity (Gauthier-Loiselle and Hunt 2008).

In this paper we use a production-function representation of the economies of U.S. states to analyze the impact of immigration on the inputs to production, on productivity and, through these, on income per worker. While a large literature has analyzed the effects of immigration on native employment, hours worked¹ and wages, using labor market data, our contribution is to identify the impact of immigration on total factor productivity and the skill-bias of aggregate productivity using national accounting data combined with census data. As for the difficulty of establishing a causal link between immigration and economic outcomes due to simultaneity and omitted variable biases, we take a two-pronged approach. First, we identify some state-characteristics more likely to be related to immigration and less to other determinants of productivity. Following Peri and Sparber (2009) we use two sets of variables as instruments. One is the distance from the Mexican border (interacted with decade dummies) that is correlated with the inflow of Mexicans, the second is the imputed number of immigrants inferred from the prior presence of immigrant communities as revealed by the 1960 census. These variables together provide variation that is a strong predictor of immigrant inflow over the period, but a priori (as they are essentially geography-based) much less correlated with other productivity shocks. Second we introduce proxies for some of the relevant causes of productivity growth in the last few decades. Treating these as potentially endogenous, and using the same instruments, we isolate the features of geography that are uncorrelated with those factors while still correlated with immigration and use them as predictors of immigrant inflows. The factors that we explicitly control for are the intensity of R&D, the adoption of computers, the openness to international trade as measured by the export intensity and the sector-composition of the state as measured by the productivity, employment and gross product growth imputed to a state on the basis of its sector composition. Both the positive and significant effect of immigration on total factor productivity and the large, negative and significant effect of immigration on the skill bias of productivity survive the instrumental variable strategy and the inclusion of these controls. We need, however, to take caution in interpreting the results causally because some lingering correlation, due to omitted variables, may remain. In particular while the positive association between immigrants and productivity growth survives the inclusion of several controls, the estimated standard errors are large. Moreover the inclusion of all controls simultaneously reduces much the power of the instruments and eliminates the statistical significance of the relation between immigrants and productivity. Our estimates are consistent with the interpretation that more immigrants in a state stimulate its

productivity growth but it is hard to rule out a spurious correlation driven by unobserved productivity shocks.

We also show that a measure of task-specialization of native workers induced by immigrants explains one third to one half of the positive productivity effect, while the effect on unskilled-biased technological adoption survives all controls. This is consistent with a state-level choice of skill-directed technology as first pointed out by Lewis (2005) and then by Beaudry, et al. (2006). These results suggest that these productivity gains may be associated with the efficient allocation of skills to tasks, as immigrants are allocated to manual-intensive jobs, pushing natives to perform communication-intensive tasks more efficiently. Hence the efficiency gains that we measure are likely to come from specialization, competition and choice of appropriate techniques in traditional sectors.

The rest of the paper is as follows: Section 2 introduces the production-function approach that we use to decompose the effects of immigration on inputs and productivity. Section 3 describes how each state-level variable is constructed and presents summary statistics for the period 1960-2006. Section 4 shows the OLS and 2SLS estimates of the effect of immigration on inputs, total factor productivity and productivity skill-bias and performs several robustness checks with respect to the effect of immigration on productivity. Section 5 provides some concluding remarks.

2 Production Function and Accounting Framework

We consider each U.S. state s in year t as producing a homogeneous, perfectly tradeable output, using the following production function,

$$Y_{st} = K_{st}^\alpha [X_{st} A_{st} \phi(h_{st})]^{(1-\alpha)} \quad (1)$$

In expression (1), Y_{st} indicates total production of the numeraire good; K_{st} measures aggregate physical capital; X_{st} measures aggregate hours worked; $A_{st}^{(1-\alpha)}$ captures total factor productivity; and $\phi(h_{st})$ is an index of skill intensity defined by the following formula:

$$\phi(h_{st}) = \left[(\beta_{st} h_{st})^{\frac{\sigma-1}{\sigma}} + ((1-\beta_{st})(1-h_{st}))^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad (2)$$

where $h_{st} = H_{st}/X_{st}$ is the share of total hours worked (X_{st}) supplied by highly educated workers (H_{st}) and $(1-h_{st}) = L_{st}/X_{st}$ is the share of total hours worked supplied by less educated workers (L_{st})². The parameter β_{st} captures the degree of skill-bias of the productivity used in state s and year t ³. In such a production function, more and less educated workers combine their labor inputs in a Constant Elasticity of Substitution (CES) function, where the elasticity of substitution is $\sigma > 0$. In order to decompose the growth rate of output per worker it is convenient to re-write (1) in terms of output per worker $y_{st} = Y_{st}/N_{st}$ (where N_{st} is total

employment in state s and year t) as follows:

$$y_{st} = \left(\frac{K_{st}}{Y_{st}} \right)^{\frac{\alpha}{1-\alpha}} [x_{st} A_{st} \phi(h_{st})] \quad (3)$$

In equation (3) $x_{st} = X_{st}/N_{st}$ captures average hours worked per person and $\frac{K_{st}}{Y_{st}}$ is the capital-output ratio⁴. Taking the logarithmic derivative over time (growth rate) of both sides of equation (3) and expressing them with a $\widehat{}$ we get⁵:

$$\widehat{Y}_{st} = \widehat{N}_{st} + \widehat{y}_{st} = \widehat{N}_{st} + \left(\frac{\alpha}{1-\alpha} \right) \widehat{\frac{K_{st}}{Y_{st}}} + \widehat{A}_{st} + \widehat{x}_{st} + \widehat{\phi}_{st} \quad (4)$$

Expression (4) is the basis of our empirical decomposition. It says that total output in a state increases as a consequence of increased employment (\widehat{N}_{st}) and of increased output per worker (\widehat{y}_{st}) which, in turn, increases due to the contribution of four factors: (i) the capital intensity $\widehat{\frac{K_{st}}{Y_{st}}}$, (ii) the total factor productivity \widehat{A}_{st} , (iii) the average hours worked \widehat{x}_{st} and (iv) the productivity-weighted skill-intensity index, $\widehat{\phi}_{st}$. The neoclassical growth model predicts that in the long run (balanced growth path) output per worker, y_{st} , only grows because of total factor productivity growth ($\widehat{A}_{st} > 0$) while the other terms ($\frac{K_{st}}{Y_{st}}$, x_{st} and ϕ_{st}) are constant. Hence a simple, exogenous increase in employment, as immigration is often considered, would only increase \widehat{N}_{st} with no long-run effect on any other variable nor on y_{st} . However, immigration can be more than a simple inflow of people. On the positive side, differences in skills, increased competition, changes in the specialization of natives and directed technical change can promote increases in productivity and capital intensity. On the negative side, crowding of fixed factors and incomplete capital adjustment can produce decreases in productivity and capital intensity. With our approach we can analyze the impact of immigration on each of the five terms on the right hand side of (4).

Our empirical approach entails estimating the impact of immigration on each term on the right hand side of equation (4). First, using measures of Gross State Product (GSP), capital stocks, hours worked, employment and relative wages of more and less educated workers, we can calculate each term on the right hand side of equation (4). Then, if we can identify an inflow of immigrants exogenous to the receiving state economies (driven, that is, by factors that are not correlated with productivity, employment or physical capital) we can estimate the elasticities η_b from the following type of regression:

$$\widehat{b}_{st} = d_t + d_s + \eta_b \frac{\Delta N_{st}^F}{N_{st}} + \varepsilon_{st} \quad (5)$$

where b_{st} is alternatively the total employment (L_{st}), the capital-output ratio $\frac{K_{st}}{Y_{st}}$, total factor productivity A_{st} , average hours worked x_{st} or the index of skill intensity ϕ_{st} . The explanatory variable $\frac{\Delta N_{st}^F}{N_{st}}$ is the percentage change in employment due to immigrants (N_{st}^F) and d_t, d_s and ε_{st} are, respectively, year fixed effects, state fixed effects and zero-mean random shocks. These regressions produce estimates that can then be aggregated to obtain

the effect on total income and on income per worker⁶. Clearly, identifying an exogenous inflow of immigrants and ensuring that immigration, and not other unobservable shocks, is driving the estimated elasticity is crucial to our goal. For these reasons we will discuss the instrumental variable strategy and the validity of the instruments at length and will introduce controls for other long-run technological and specialization trends in section 4.

3 Construction of Variables and Summary Statistics

We consider as the units of analysis fifty U.S. states plus Washington D.C. in each census year between 1960 and 2000 and in 2006. We use three main data sources. For data on aggregate employment and hours worked, including the distinction between more and less educated workers and natives and immigrant workers, we use the public use micro-data samples (IPUMS) of the U.S. Decennial Census and of the American Community Survey (Ruggles et al., 2008). For data on GSP we use the series available from the Bureau of Economic Analysis (2008b). Finally, to calculate state physical capital we use data from the National Economic Accounts, obtained from the Bureau of Economic Analysis (2008a). We now describe the construction of each variable in detail.

To construct employment and hours worked⁷ we use Census Data⁸. Since they are all weighted samples we use the variable “personal weight”(PERWT) to produce the aggregate statistics. We divide workers into the two education groups H (those with some college education or more) and L (those with high school education or less). The “foreign-born” status used to identify native and immigrant workers is given to those workers who are non-citizens or are naturalized citizens⁹.

The hours of labor supplied by each worker are calculated by multiplying hours worked in a week by weeks worked in a year and individual hours are multiplied by the individual weight 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, of domestic (native) and foreign-born 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-born 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, consistent with the model below, we call $X_{st} = X_{st}^D + X_{st}^F$ the total hours supplied by workers of both education levels (sum of H and L) in state s and year t ; $N_{st} = N_{st}^D + N_{st}^F$ denotes the total employment (sum of natives and foreign born) in state s and year t ;

We measure gross product at the state level Y_{st} using data on GSP available from the Bureau of Economic Analysis (2008a). The Bureau of Economic Analysis produces figures on GSP in current dollars. The currently available series covers the period 1963-2006. We use that series and convert it to constant 2000 dollars 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 in order 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 D.C. The variable y_{st} , output per worker, is then constructed by dividing the real GSP Y_{st} by total employment in the state, N_{st} .

The construction of physical capital K_{st} is a bit more cumbersome. The National Economic Accounts only estimates the stock of physical capital by industry at the national level¹⁰. Following Garofalo and Yamarik (2002) we use the national estimates of the capital stock over the period 1963-2006 for 19 industries (listed in the Online Appendix 2). We then distribute the national capital stock in a year for each industry across states in proportion to the value added in that industry that is 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 the 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 the panel of real capital stock values by state K_{st} . Capital per worker ($k_{st} = K_{st}/N_{st}$) is calculated by dividing the capital stock by total employment in the state and year. Hence, in total, we can obtain direct measures of the variables $Y_{st}, N_{st}, X_{st}, H_{st}, L_{st}$ and of the ratios y_{st}, x_{st} and h_{st} .

The variables A_{st} and β_{st} are not observed directly. However, we can use the production function expression in (1) and the condition that the average hourly wage of more and less educated (w_{st}^H and w_{st}^L) equals the marginal productivity of H_{st} and L_{st} , respectively, to obtain two equations in two unknowns and solve them. In particular, setting the ratio of the hourly wages of H_{st} to L_{st} equal to the ratio of their marginal productivity gives the following equation:

$$\frac{w_{st}^H}{w_{st}^L} = \left(\frac{\beta_{st}}{1 - \beta_{st}} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{h_{st}}{1 - h_{st}} \right)^{-\frac{1}{\sigma}} \quad (6)$$

Solving (6) for the parameter β we obtain the following expression:

$$\beta_{st} = \frac{(w_{st}^H)^{\frac{\sigma}{\sigma-1}} h_{st}^{\frac{1}{\sigma-1}}}{(w_{st}^H)^{\frac{\sigma}{\sigma-1}} h_{st}^{\frac{1}{\sigma-1}} + (w_{st}^L)^{\frac{\sigma}{\sigma-1}} (1 - h_{st})^{\frac{1}{\sigma-1}}} \quad (7)$$

Substituting (7) into (1) and solving explicitly for A_{st} we obtain:

$$A_{st} = \left(\frac{Y_{st}^{\frac{1}{1-\alpha}} K_{st}^{-\frac{\alpha}{1-\alpha}}}{X_{st}} \right) \frac{(w_{st}^H)^{\frac{\sigma}{\sigma-1}} h_{st}^{\frac{1}{\sigma-1}} + (w_{st}^L)^{\frac{\sigma}{\sigma-1}} (1-h_{st})^{\frac{1}{\sigma-1}}}{[w_{st}^H h_{st} + w_{st}^L (1-h_{st})]^{\frac{\sigma}{\sigma-1}}} \quad (8)$$

The only new variables required to calculate β_{st} and A_{st} , besides those described above, are the hourly wages for more and less educated workers, w_{st}^H and w_{st}^L . We obtain these from the IPUMS data by averaging hourly wages by state and year separately for individuals with some college education or more, w_{st}^H , and for those with high school education or less, w_{st}^L ¹¹. Finally, in order to implement (7) and (8) we need a value for the parameter σ , the elasticity of substitution in production between more and less educated workers and for the parameter α , the elasticity of output to capital. As there are several estimates of σ in the literature, most of which cluster between 1.5 and 2.0 (see Ciccone and Peri, 2005 for a recent estimate and a survey of previous ones), we choose the median value of 1.75 for σ and check the robustness of our most relevant results to a value of 1.5 and of 2.0. As for α we consider the value of 0.33 that is commonly used in exercises of growth accounting and is based on the value of one minus the share of income to labor (usually estimated around 0.67, e.g. Gollin 2002).

The average growth rates, by decade, of all the variables described above are reported in Table A1 of the Online Table Appendix. Some well known tendencies are evident in the data. The progressive increase in the inflow of immigrants as a share of employment during the 70's and again during the 90's is noticeable. We also see the slow-down in total factor productivity during the 70's and 80's and the re-acceleration during the 2000-2006 period. Employment and working hours per person experienced sustained growth over the entire 1970-2000 period with a reduction only in the 2000-2006 period. The last two rows of Table A1 show that both the skill-bias of technology, β_{st} , and the share of highly educated workers, h_{st} , increased constantly and significantly over the whole period and in particular during the 70's and 80's. The literature on wage dispersion across education groups (e.g., Katz and Murphy 1992; Autor et al. 2008) has emphasized this finding, attributing it to directed skill-biased technological change. Reassured by the behavior of our measured and constructed variables, which match some important trends emphasized in the literature, we proceed to the empirical analysis.

4 Estimates of the Effects of Immigrants

4.1 OLS Estimates

Our main empirical strategy is to estimate equations like (5) using, alternatively, the growth rate of different variables in lieu of the placeholder \hat{b}_{st} . The dependent variables used in the regressions are shown in the first column of Tables 1 and 2, and the estimated elasticity (η_b) is reported in the cells of those tables. As introductory results, Table 1 reports the OLS estimates of equation (5) on a panel of 50 U.S. states (plus D.C.)

using inter-census changes between 1960 and 2000 and the 2000-2006 change. Each cell reports the result of a different regression that includes time and state fixed effects, weights each cell by the total employment in it, and reports the heteroskedasticity-robust standard errors clustered by state to account for potential correlation of the residuals over time. The first two rows of Table 1 decompose the effect of immigration on total income into its effect on total employment (\widehat{N}_{st}) and on output (gross state product) per worker (\widehat{y}_{st}). The following four rows decompose the effect on output per worker into the contributions due to the capital intensity $\left(\frac{\alpha}{1-\alpha}\right)\frac{\widehat{K}_{st}}{\widehat{Y}_{st}}$, total factor productivity, \widehat{A}_{st} , average hours worked \widehat{x}_{st} , and the skill-intensity index $\widehat{\phi}_{st}$. Those four effects add up to the total effect on \widehat{y}_{st} ¹². Finally, the last two rows show the effect of immigration on the share of educated workers \widehat{h}_{st} and on the skill-bias of productivity $\widehat{\beta}_{st}$ both of which enter the expression for the skill-intensity index $\widehat{\phi}_{st}$. Estimating the effect via OLS including time and state fixed effects accounts for common US cycles specific to each decade and for state-specific trends in income and immigration. However these estimates are still potentially subject to endogeneity and omitted variable biases. We propose an estimation strategy that addresses those issues in the next sections.

Nevertheless Table 1 shows some evidence of stable and significant correlations between net immigration and some of the relevant growth rates. In particular, we also check whether the correlations depend on the period considered (in column 2 we drop the 60's and in column 3 we drop the 2000's), and whether including the lagged dependent variable in order to capture auto-correlation over time (column 4) or instrumenting immigrant employment changes with immigrant population changes (column 5) affects the estimates.

The estimates are quite stable across specifications¹³ so we can simply comment on the general features of these correlations. First, the elasticity of total employment to immigrants is always larger than one (sometimes as large as two) and never significantly different from one. This confirms previous studies, such as Card (2001, 2005), Ottaviano and Peri (2006) and Peri and Sparber (2009), that report no evidence of crowding-out of native employment by immigrants using correlation across local labor markets¹⁴. The estimates are often much larger than one, potentially suggesting the existence of a demand-driven bias. Second, the coefficients in the second row show that there is a positive and sometimes significant correlation between income per worker and immigration. This positive correlation results from the combination of a large positive and significant correlation between immigration and total factor productivity (fourth row of Table 1), and a small negative and insignificant correlation between immigration and capital intensity (third row of Table 1). The positive correlation of immigrants with average hours worked (ranging from +0.09 to 0.29) and their negative correlation with the average skill index $\widehat{\phi}_{st}$ (between -0.11 and -0.26) compensate for each other in terms of income per worker.

Finally, we also find a very significant negative correlation between the immigration rate in employment and both the share of more educated workers and the skill-bias of technology, both with an elasticity within (or close

to) the range -0.7/-1.0. States with larger than average inflows of immigrants over the period 1960-2006 were therefore associated with a more than one-for-one increase in employment, a larger growth of income per worker (entirely due to larger TFP growth), while at the same time the skill intensity and the skill-bias of production grew at a slower rate.

4.2 Instruments and 2SLS

Our instrumental variable approach combines the instruments based on the past settlement of immigrants (augmented by their national rate of growth) drawn from Card 2001, and then used in several other studies (including Card 2009 and Peri and Sparber 2009), with a purely geographical instrument based on the distance from the border between Mexico and the US. Specifically, 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 from 10 different areas¹⁵. For each nationality of origin and each state the total number of people in working age (16-65) in Census 1960 is augmented in 1970 to 2006 by applying the decade national growth rate of the population from that nationality in the whole US. This allows us to impute the immigrant population from each nationality of origin in each state that we then add up across nationalities within a state to construct the imputed decennial growth of working age population due to imputed immigrants. The variation of such measure across states depends only on the initial presence of immigrants (as of 1960) and on their national composition and is independent of any subsequent state-specific economic factors. We use this measure as an instrument for the growth in employment due to immigrants in each state and decade, $\frac{\Delta N_{st}^F}{N_{st}}$.

The US-Mexico border (for Mexican immigrants) is the main point of entry to the U.S. The distance of each state's center of gravity from the Border is first calculated. We then 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 immigration¹⁶.

The imputed immigrants and time-interacted border-distance have significant power in predicting immigration. Their F-test in the samples is usually around 17 when used jointly (see the second to last row in Table 2). Even the border-distance instruments by themselves have significant power (F-test of 13, as reported in the last column of Table 2). The imputed immigrants by themselves, however, have only a weak power (F-test of 6.77) and hence we cannot use that instrument by itself. Importantly the instruments, when used jointly, pass the test of overidentifying restrictions and one cannot reject the assumption of exogeneity of instruments at 1%, 5% or 10% confidence level¹⁷. Surveying the results across specifications, again using different samples (omitting 1960 in specification 2 and 2006 in specification 3), controlling for past lagged values (specification 4), and using only the set of instruments based on the Mexican border-distance (specification 5) we obtain a rather consistent picture. First, the impact on total employment is now estimated to be close to one and never

statistically different from one. This confirms the idea that some reverse causality may bias the OLS estimates of the employment effects up. The effect on the growth of income per worker is similar than in the OLS case and significant except for specification (4) and mostly between 0.7 and 1. The standard errors, always clustered by state to account for potential auto-correlation of the errors over time, are sometimes large enough to make the estimates only marginally significant. Decomposing this effect one sees that the positive elasticity of income per workers to immigration results mainly from the positive effect on TFP. The estimated effects on capital intensity (usually insignificant) on average hours worked (usually positive) and on the skill index (usually negative) roughly balance each other.

As in the estimates of Table 1 the negative coefficient of immigration on the skill index $\hat{\phi}_{st}$ is roughly balanced by the positive effect on hours worked and so those two terms contribute very little to output per worker. The negative effects of immigration on the share of highly educated workers and on the skill-bias of technology are strongly confirmed by the 2SLS estimates and in both cases the elasticity is around -1. One should still be very careful in interpreting the coefficient as causal, as the instruments could be correlated with economic factors affecting productivity and growth in a state-decade¹⁸. The estimates, however, are consistent with three effects of immigration: one is well known but two have not been clearly identified by the existing literature. First, immigration mechanically increases employment and reduces its share of highly educated workers, and it does not crowd out native employment. These are well-known effects already emphasized by Card (2007) and Card and Lewis (2007). Second, immigration promotes production techniques that are more unskilled-efficient (as suggested by Lewis, 2005, and consistently with the idea of directed technological choice). Finally immigration is also associated with faster growth in overall factor-neutral productivity.

The most interesting estimates are those regarding total factor productivity and its skill bias. The first is responsible for the significant net positive effect of immigrants on output per worker and the second is a direct test of directed technical adoption. Hence, we will devote section 4.3 to testing their robustness to the inclusion of several controls. Before doing that let us remind the reader that the zero effect of immigration on capital intensity (capital-output ratio) in the long-run (10 year intervals) is consistent with the idea that US states have been growing along their balanced growth path: increased employment and higher productivity were matched by investments to guarantee a constant capital-output intensity. This is what is predicted by a simple neoclassical growth model.

4.3 The Effects on Productivity and Skill-Bias

The most remarkable and novel effects estimated in Table 2 are the positive and significant effect of immigration on total factor productivity (\hat{A}) and the negative and significant effect on the skill-bias of technology ($\hat{\beta}$). Both effects are quite large and while they are not estimated extremely precisely they are usually significant. The

concern is that the geographic location of a state used in constructing the instrument in the 2SLS estimation, while certainly affecting the immigration rates and exogenous with respect to technological changes, may be correlated with other features that have affected productivity growth and its skill-intensity. For these reasons, while keeping the border distance and the imputed immigration as instruments (we need both of them for sufficiently powerful instruments) we include in the regression several variables that are aimed at capturing other influences on the productivity and technology of U.S. states. We include each of them, one by one, considering them as potentially endogenous and therefore using the border-distance and imputed-immigrant instruments to predict them.

The coefficients on the control variables are sometimes estimated imprecisely (and we do not report them in Tables 3 and 4); however, what we care about is the coefficient on the immigration rate, estimated using the instruments. The inclusion of the controls implies that *we are using the variation in the instruments that is orthogonal to the controlled factor* (and hence independent from it) to predict the immigration rate and to estimate its effect on productivity. We include the controls one at the time. Including them all together and treating them as potentially endogenous reduces the power of the instrument drastically, producing very large standard errors. Table 3 shows the estimated coefficients on the immigration rates in regressions based on (5), using \widehat{A}_{st} as the dependent variable. Table 4 shows the coefficients of similar regressions with $\widehat{\beta}_{st}$ as the dependent variable. Proceeding from top to bottom, Tables 3 and 4 show estimates obtained using OLS (first row) or 2SLS estimation methods (rows 2 to 5). Moreover, to check how robust the results are to the choice of the parameter σ (the substitutability between more and less educated workers) in the construction of \widehat{A}_{st} and $\widehat{\beta}_{st}$ we report the estimates using two alternative values of that parameter (equal to 1.5 and 2, respectively). We also report in the third row of Table 3 the results obtained when using the more standard formula for the “Solow¹⁹ residual” in order to compute \widehat{A}_{st} ²⁰. The last two rows of Tables 3 and 4 report results from a specification that we will discuss in section 4.4.

Considering the different specifications (columns) in Table 3 (and Table 4), we first report the basic estimates obtained from a regression that only controls for time and state fixed effects, then column (2) controls for the average real yearly R&D spending per worker in each state in the 70’s, 80’s, 90’s. and 2000’s²¹. We obtain the variable by dividing the aggregate state expenditures by state employment. The estimated effect of the R&D variable on TFP changes (not reported) corresponding to the second row of specification (2) is 0.10 (with a standard error equal to 0.09) while its effect on $\widehat{\beta}_{st}$ is 0.04 (with standard error 0.10). So the R&D variable positively affects both productivity and skill-bias, which is expected. More importantly for our purposes, the inclusion of R&D as a control does not affect much the estimated effect of immigration on TFP (with an elasticity of 1.02 in the 2SLS specification) and on the skill-bias (an elasticity of -0.84).

The third column of Tables 3 and 4 introduces computer use as a control. The adoption of computer

technology was a major technological innovation leading to increased productivity and since its diffusion varied by sector and location we can control for it. To do this we include the change in share of workers using the computer (computer adoption) in specification (3)²². The estimated coefficient of the computer adoption variable on \hat{A}_{st} (not reported) is 2.10 (standard error 0.90) while on $\hat{\beta}_{st}$ it is 0.21 (standard error 0.16)²³. As expected, computer adoption has a positive and skill-biased effect on productivity across states. More interesting for us is that the effect of immigration on \hat{A}_{st} is still positive and significant (but reduced by about 40% from its basic estimate to an elasticity of 0.88) and the effect on the skill-bias is essentially unchanged in its magnitude (-1.01) and significance (standard error equal to 0.18).

The geographic location of an economy is an important determinant of its trade with the rest of the world. Being close to a major port, to the coast and its distance from other countries all affect trade costs and hence trade volumes. Moreover, during the decades between 1980 and 2006 the U.S. significantly increased its trade with the rest of the world. Since trade may increase productivity (promoting competition, inducing specialization, reducing costs of inputs) we control for trade as a share of GSP in order to account for this effect²⁴. We calculate exports as a share of GSP in 1987-1989 and attribute this value to the entire decade of the 1980's and then calculate the average export/GSP value by state in the 1990's and in the 2000-2006 period. We include these values in the regression as a proxy for the access of a state to international trade in each decade. Two things are important to notice. First proximity to the Mexican border is not a very good predictor of increase in trade (the F-test of the border-distance instrument in predicting trade over the considered decades is only 2.56). Second trade with Asia, Europe and Canada has been each larger (in value) than trade with Mexico. Hence while the geographic location of a state affected its trade the *specific distance from the Mexican border* did not have much correlation with trade growth. The coefficient obtained for the effect of trade on productivity (not reported) is negative (-0.15) and not significant (standard error 0.20) while the effect on the skill-bias is also negative and not significant. When trade is included as a control (Column 4) immigration maintains a positive and very significant effect on productivity (+1.17 reported in Table 3), as well as a negative and largely unchanged effect on the productivity bias (-0.89 as reported in Table 4).

Finally, the last column of Tables 3 and 4 introduces a control that accounts for the sector-composition of each state and its effect on productivity. In particular, we construct and include in the regression the sector-driven productivity growth by averaging the national growth rate of total factor productivity in each of 14 sectors²⁵, each weighted by the initial (1960) share of that sector in the State Value added (from Bureau of Economic Analysis 2009)²⁶.

This control accounts for the fact that different states had different sector structures in 1960 and this might be correlated with the presence of immigrants back in 1960 (or with the geographic location of the state) invalidating the exclusion restriction. The inclusion of this sector-based productivity growth (whose coefficient

on TFP is positive and very significant) does not modify much the effect of immigration on \widehat{A}_{st} and on $\widehat{\beta}_{st}$. The impact of immigrants on \widehat{A}_{st} including this control is 0.82 (standard error 0.31) – see column (5) of Table 3– and the impact on the skill-bias of technology is -1.11 (with a standard error of 0.16)– see Column (5) of Table 4. The (unskilled-biased) productivity effect of immigrants is quite robust to the inclusion of several controls.

4.4 The Task-Specialization Hypothesis and Robustness Checks

Two mechanisms proposed and studied in the previous literature can jointly explain the positive productivity effect of immigrants and its skill-bias. Lewis and Card (2007) find that in markets with an increase in less educated immigrants a large proportion of all sectors show a higher intensity of unskilled workers. Furthermore, Lewis (2005) documents that in those labor markets there is a slower adoption of skill-intensive techniques. This is in accordance with the theory of “directed technological change” or “appropriate technological adoption” (Acemoglu 2002) in which the availability of a production factor pushes firms to adopt technologies that are more efficient and intensive in the use of that factor. More recently, in a paper with Chad Sparber (Peri and Sparber 2009) we show that in states with large inflows of immigrants, natives with lower education tend to specialize in more communication-intensive production tasks, leaving to immigrants more manual-intensive tasks. This produces increased task-specialization following comparative advantages and results in efficiency gains especially among less educated workers. In the last two rows of Table 3 we analyze whether the reorganization of production around the efficient specialization of natives (and immigrants) can explain part of the measured productivity gains.

We include in the regression a measure of the change in relative specialization of less educated natives between communication and manual tasks at the state level. The variable is constructed (as described in Peri and Sparber 2009) by attributing the intensity of physical-manual tasks (M_i) and of communication-interactive (C_i) tasks to each worker, i , based on their occupation, using the average of 52 ability variables collected in the US Department of Labor’s O*NET dataset²⁷. Then we calculate the average of the ratio of these two task intensities for less educated native workers in each state s and year t , C_{st}/M_{st} . The percentage change in this variable measures the change in task-specialization of natives and is then included in the regression. The idea is that if immigrants affect the efficiency of production in a state, by reallocating natives toward communication tasks and by undertaking manual tasks, leading to an overall productivity improvement, we should observe the productivity effect of immigrants mostly through the task-reallocation of natives. Hence, controlling for this task reallocation the productivity impact of immigrants should decrease. Moreover, the instruments used to predict immigrant flows should also be good instruments for the endogenous task reallocation. This is what we observe in the last two rows of Table 3, where we report the coefficients on the immigration variable and on the native specialization change, estimated by 2SLS and also including the other controls.

Two patterns emerge. First, the estimated coefficient on the change in specialization is positive and sometimes significant—in other words, the specialization change instrumented by geography has a positive effect on productivity²⁸. Second, the coefficient on the immigration variable, while still positive, is reduced significantly, often to half of its original estimate (considering as reference the 2SLS estimates without a control for specialization). It also loses its significance in all cases. Hence, the effect of controlling for the “change in specialization” on the estimated coefficient of immigration on TFP is much more drastic than the effect of introducing any other control. This is evidence that a least part of the effect of immigrants on productivity comes from the re-allocation of natives and immigrants across production tasks. Table 4 shows that the effect of controlling for task re-allocation on the skill-bias regression is much smaller (coefficient reduced by 5 to 10% in absolute value). Reallocation is likely to enhance overall efficiency. However, controlling for task re-allocation, states with a large inflows of immigrants are still likely to choose relatively unskilled-intensive (and perhaps manual-intensive) techniques.

Finally, Table 5 shows the robustness of the main estimated coefficients (on \widehat{N}_{st} , \widehat{y}_{st} , \widehat{A}_{st} and $\widehat{\beta}_{st}$) to further controls and sample restrictions. First, especially for GSP and productivity, one may suspect that convergence across states may bias the estimates if immigrants tend to flow into states that are catching-up with the economic frontier. Hence growth rates may depend on the initial level of the variables. Including the initial value of the dependent variable to account for convergence and omitting fixed state effects²⁹ (column 2 of Table 5) does not change any qualitative result; it only increases the estimated positive impact of immigration on employment while it decreases somewhat the effect on GSP per worker and productivity.

If we eliminate the Mexican border states in specification (3), the explanatory power of the instruments is reduced as is evident in the larger standard errors. However, all the effects, though very imprecise, are positive, significant and much larger than in the basic sample. The standard errors and the point estimates also increase when we eliminate the largest state economies (California, Texas and New York), which are also the largest receivers of immigrants (specification 4). Restricting the sample to only the three most recent decades, which experienced by far the largest aggregate inflow of immigrants (specification 5) does not change the results. Finally, including the sector-based imputed growth of the dependent variable (\widehat{N}_{st} , \widehat{y}_{st} , \widehat{A}_{st} or $\widehat{\beta}_{st}$) constructed using the national growth rate of the relevant variable in 13 industries and then weighting those growth rates by the 1960 share of that industry in state value added³⁰ (specification 6) does not change the estimate much either.

5 Conclusions

This paper uses an aggregate accounting approach to analyze the relation between immigration and employment and productivity of US state economies. While the aggregate nature of the data and the impossibility of

identifying a genuinely random variation of immigration flows call for caution in the causal interpretation of our estimates, we present three interesting findings, two of which are new in this literature. First, we confirm that there is no evidence that immigrants crowd-out employment of (or hours worked by) natives. Second, we find that immigration is significantly associated with total factor productivity growth. Third such efficiency gains are unskilled-biased — larger, that is, for less educated workers. These correlations are robust to including several control variables individually (such as R&D spending, technological adoption, sector composition, openness to international trade or sector composition) and they are not explained by productivity convergence across states nor driven by a few states or particular decades. We conjecture that at least part of the positive productivity effects are due to an efficient specialization of immigrants and natives in manual-intensive and communication-intensive tasks, respectively (in which each group has a comparative advantage), resulting in an overall efficiency gain. Preliminary empirical evidence supports this claim. The positive coefficient from the 2SLS estimates imply that net inflow of immigrants, even those driven by their historical location and proximity to the border, are associated with significant productivity gains for the receiving states.

Notes

¹Card (2007, 2009) discuss the status of this literature.

²The definitions imply that $L_{st} + H_{st} = X_{st}$.

³In (1), if we carry the terms X_{st} and A_{st} inside the index $f(h_{st})$ and we call $A_{st}^H = \beta_{st}A_{st}$ and $A_{st}^L = (1 - \beta_{st})A_{st}$ we obtain a common production function used in several studies of aggregate labor markets (e.g. Katz and Murphy 1992, Card and Lemieux 2001), of income distribution (Krusell et al. 2000) and of technological growth (Acemoglu 1998, Caselli and Coleman 2006).

⁴In the balanced growth path of any neoclassical model the capital-output ratio is constant due to the linearity of the physical capital accumulation equation in K_{st} and Y_{st} (see for instance page 99 of Barro and Sala i Martin, 2004)

⁵For any variable b , $d \ln b / dt = \widehat{b}$

⁶If immigration has some effect on productivity and/or capital intensity then differential immigration can drive differences in productivity and wages across states. Because of worker mobility, these differences will push all workers into states with higher productivity. To avoid this, we assume that, while in terms of production-prices (in units of the numeraire) permanent differences in income per person could arise, these are absorbed by corresponding differences in the average price index across states, driven by differences in the prices of housing or fixed amenities. This is compatible with an equilibrium where workers are mobile. The large literature that documents a strong positive effect of immigration on housing prices (such as Saiz, 2003, 2007, Ottaviano and Peri, 2006, Gonzales and Ortega, 2009) confirms that this adjustment mechanism, through land prices and local price indices, is plausible.

⁷The details on variable definition, construction and data are contained in the Online Appendix.

⁸Specifically 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) for the year 2006.

⁹To identify foreign-born we use the variable "CITIZEN" beginning in 1970 and "BPLD" in 1960

¹⁰See the Online Appendix for a detailed description.

¹¹The exact procedure used to calculate individual hourly wages is described in the Online Appendix.

¹²This is true, by construction, for the OLS estimates of Table 1 but not for the 2SLS estimates of Table 2.

¹³The specification that produces estimates farther from the others is the one including the lagged dependent variable in column (4). As we include fixed effects, these panel estimates are subject to the bias emphasized by Nickell (1981).

¹⁴Given the way we constructed our variables, a coefficient of one on \widehat{N}_{st} implies that one immigrant worker produced an increase in total employment of one, hence it produces no change in native employment.

¹⁵The "nationality of origin" that we consider are the following: Mexico, Rest of Latin America, Canada-Australia-New Zealand, Western Europe, Eastern Europe and Russia, China, India, Rest of Asia, Africa and Others.

¹⁶A more detailed description of how these instruments are constructed can be found in Peri (2009).

¹⁷The test statistic, under the null hypothesis that none of the instruments appear in the second stage regression, is distributed as a Chi-square with degrees of freedom given by the difference between the number of instruments and the endogenous variables (5 in our case). The test statistics equals 7.65. The corresponding p-value for the relevant Chi-square distribution, with 5 degrees of freedom, is 0.18, and hence the null hypothesis of exogenous instruments stands at 10% confidence. See Wooldridge (2002) for the details of the test.

¹⁸We will control for several of these state-specific factors in Section 4.3.

¹⁹As it is described in Solow (1957).

²⁰The formula (8) reduces to that of the Solow residual when $\sigma = \infty$.

²¹The data are from the National Science Foundation (1998) and include total (private and federal) funds for industrial R&D in constant 2000 US dollars. The data are available every year for the period 1975-2006. We calculate the average yearly expenditure in a state between 1975 and 1979 and we impute it over the whole 70's decade. In the following periods we use the average yearly expenditure during the period.

²²The original (individual) data are from the March supplement of the Current Population Survey, and are available for the years 1984, 1997, 2001. Assuming that in 1960 and 1970 no worker used a computer, since the PC was first introduced in 1980, we interpolate linearly the 3 data points and we impute the shares of workers using computers in 1980, 1990, 2000 and 2006 for each state.

²³In both cases these are the coefficients from the basic 2SLS specification in the second row.

²⁴The data on exports of manufactured goods by state of origin are from the Origin of Movement data

available from the US Census and for purchase on CD-ROM (at www.gtis.com). These data are the total value, in current dollars, of exports from each state from 1987 to 2006.

²⁵These sectors are: Agriculture, Agricultural services, Mining, Construction, Manufacturing of Durable goods, Manufacturing of Nondurable goods, Transportation, Communications- Electric-Gas, & sanitary utility, Wholesale trade, Retail trade, F.I.R.E., Other Services, Government.

²⁶The data on Sector-specific TFP are calculated using data on Value added and Capital Stocks from Bureau of Economic Analysis (2008b), deflated to 2000 US \$ using the GDP and Investment price deflator, respectively and Employment by industry also obtained from Bureau of Economic Analysis (2008b) (merging the SIC codes before 1997 and the NAICS codes from 1998). We apply a simple growth accounting method to construct the Solow residual in each industry using a share of labor equal to 0.66.

²⁷For a list and classification of Abilities into Manual and Communication skills see table A1 of Peri and Sparber (2009).

²⁸If we only include the change in task specialization of natives and not the share of foreign-born as explanatory variable and use the same set of instruments the coefficient on that variable turns out to be always significant.

²⁹We omit fixed effects in order to avoid the bias emphasized in Nickell (1981).

³⁰The sector-based imputed growth of the dependent variables included in these regressions are the analog of those included for TFP and for skill-bias in columns 5 of Tables 3 and 4. In the regressions of the first row we include imputed employment growth as control. In the regressions of the second row we include imputed GSP growth as control. In the regressions of the third and fourth row we include the imputed TFP growth as control.

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Tables

Table 1:
OLS estimates of the impact of immigration on the components of Gross State Product growth

<i>Explanatory variable is immigration as percentage of initial employment;</i>	(1) <i>basic OLS</i>	(2) <i>1970-2006</i>	(3) <i>1960-2000</i>	(4) <i>Including Lagged Dependent variable</i>	(5) <i>2SLS estimates using Immigrant Population Change as instrument</i>
Dependent Variable:					
\hat{N}	1.76* (0.80)	2.06** (0.95)	2.32** (0.95)	2.15** (0.71)	1.73* (0.91)
\hat{y}	0.62 (0.43)	0.54 (0.47)	0.93* (0.50)	0.55 (0.36)	0.51 (0.50)
Components of \hat{y}					
$\left(\frac{\alpha}{1-\alpha}\right)(\hat{K} - \hat{Y})$	-0.13 (0.12)	-0.21 (0.15)	0.07 (0.22)	-0.18 (0.12)	-0.22 (0.17)
\hat{A}	0.80** (0.39)	0.88* (0.43)	0.68 (0.48)	0.82** (0.39)	1.08** (0.32)
\hat{x}	0.15** (0.05)	0.09 (0.05)	0.29** (0.09)	0.14* (0.07)	0.14** (0.05)
$\hat{\phi}$	-0.20** (0.05)	-0.22** (0.05)	-0.11* (0.05)	-0.26** (0.05)	-0.19** (0.06)
Components of $\hat{\phi}$					
\hat{h}	-0.75** (0.15)	-0.56** (0.15)	-0.92** (0.24)	-0.52** (0.17)	-0.73** (0.18)
$\hat{\beta}$	-0.92** (0.20)	-0.68** (0.19)	-1.19** (0.34)	-0.62** (0.19)	-0.89** (0.24)
Observations	255	204	204	204	255

Note: Each cell is the result of a separate regression. The explanatory variable is the net inflow of immigrant workers over an inter-census period as a percentage of the initial employment. The units of observations are US states (plus DC) in each decade 1960-2000 plus 2000-2006. Each regression includes time fixed effects and state fixed effects. The method of estimation is least squares with observations weighted by the employment of the state. Errors in parenthesis are heteroskedasticity-robust and clustered by state. The calculated variables use the assumption that $\sigma=1.75$ and $\alpha=0.33$. **=significant at the 5% confidence level. *=significant at the 10% confidence level.

Table 2:
2SLS estimates of the impact of immigration on the components of Gross State Product growth

<i>Explanatory variable is immigration as percentage of initial employment;</i>	(1) <i>basic 2SLS</i>	(2) <i>1970-2006</i>	(3) <i>1960-2000</i>	(4) <i>2SLS, including lagged dependent variable</i>	(5) <i>Border instrument only</i>
Dependent Variable:					
\hat{N}	1.09** (0.45)	1.39** (0.55)	1.23** (0.25)	1.94** (0.69)	1.11** (0.46)
\hat{y}	0.88** (0.25)	0.71* (0.35)	1.47** (0.30)	0.22 (0.27)	1.03** (0.34)
Components of \hat{y}					
$\left(\frac{\alpha}{1-\alpha}\right)(\hat{K} - \hat{Y})$	-0.08 (0.13)	-0.13 (0.13)	0.27 (0.23)	-0.10 (0.14)	-0.08 (0.09)
\hat{A}	1.37** (0.27)	1.11** (0.36)	0.97** (0.36)	0.61** (0.24)	1.15** (0.30)
\hat{x}	0.28** (0.11)	0.17 (0.09)	0.61** (0.19)	0.27** (0.10)	0.24** (0.08)
$\hat{\phi}$	-0.26** (0.07)	-0.29** (0.08)	-0.14 (0.11)	-0.38** (0.08)	-0.27** (0.07)
Components of $\hat{\phi}$					
\hat{h}	-1.16** (0.25)	-0.90** (0.23)	-1.58** (0.36)	-0.89** (0.20)	-1.14** (0.27)
$\hat{\beta}$	-1.14** (0.15)	-0.84** (0.13)	-1.74** (0.25)	-0.49** (0.18)	-1.08** (0.15)
First stage F-test	17.42	7.48	17.99	17.42	13.11
Observations	255	204	204	204	255

Note: Each cell is the result of a separate regression. The explanatory variable is the net inflow of immigrant workers over an inter-census period as a percentage of the initial employment. The units of observations are US states (plus DC) in each decade 1960-2000 plus 2000-2006. Each regression includes state fixed effects and year fixed effects. The method of estimation is 2SLS with imputed immigrants and distance from border interacted with decade dummies as instruments. The errors in parenthesis are heteroskedasticity-robust and clustered by state. The calculated variables use the assumption that $\sigma=1.75$ and $\alpha=0.33$.

**= significant at the 5% level; *=significant at the 10% level.

Table 3:
Estimated impact of immigration on Total Factor Productivity (\hat{A})

<i>Dependent Variable: \hat{A}</i>	(1)	(2)	(3)	(4)	(5)
<i>Explanatory variables: Immigrants as share of employment</i>	<i>Basic (1960-2006)</i>	<i>Controlling for R&D per worker (1970-2006)</i>	<i>Controlling for Computer Adoption</i>	<i>Controlling for Trade (period 1980- 2006)</i>	<i>Controlling for TFP- growth based on sector composition (1960-2006)</i>
<i>OLS</i>	0.80** (0.39)	0.90** (0.37)	0.70** (0.38)	1.05** (0.53)	0.50 (0.35)
<i>2SLS</i>	1.37** (0.27)	1.02** (0.31)	0.88** (0.26)	1.17** (0.49)	0.82** (0.31)
<i>2SLS TFP calculated as standard Solow Residual ($\sigma=\infty$)</i>	0.77* (0.41)	0.73** (0.35)	0.59* (0.29)	0.94* (0.54)	0.56* (0.30)
<i>2SLS \hat{A} constructed with $\sigma=1.5$</i>	1.72** (0.44)	1.81** (0.29)	1.70** (0.28)	1.78** (0.43)	1.53** (0.36)
<i>2SLS \hat{A} constructed with $\sigma=2$</i>	0.80* (0.41)	0.75** (0.34)	0.62** (0.29)	0.94* (0.53)	0.59* (0.31)
<i>Explanatory variables:</i>	Task specialization channel: dependent variable \hat{A}				
Change in Employment due to Immigration	0.90 (0.94)	0.51 (0.58)	0.69 (0.67)	0.51 (0.79)	0.13 (0.62)
Change in Communication- Manual specialization of natives	1.30* (1.30)	1.63 (1.68)	2.70** (1.16)	1.20 (1.00)	0.67 (1.20)
Observations	255	204	255	153	255

Note: Each cell in row 1 to 5 is the coefficient of the regression of \hat{A} on the change in employment due to immigrants, estimated including time and state fixed effects. The baseline estimate (row 1) is OLS with TFP constructed using the assumption that $\sigma=1.75$. In the second row we use 2SLS with imputed immigrants and border distance interacted with decade dummies as Instruments. In the third row we calculate the TFP as simply Solow residual without accounting for the imperfect substitution of the more and the less educated. In the fourth and fifth row total factor productivity is constructed under the assumption that σ , the elasticity of substitution between more and less educated is 1.5 or 2. In the last two rows we report the coefficient of a regression of \hat{A} simultaneously on the immigration rate and on the change in task-specialization of less educated natives. The units of observations are 50 US states plus DC in each decade 1960-2000 plus 2000-2006. The errors in parenthesis are heteroskedasticity-robust and clustered by state. **= significant at 5%, *=significant at 10%.

Table 4:
Estimated impact of immigration on Skill-Bias ($\hat{\beta}$)

Dependent Variable: $\hat{\beta}$ <i>Explanatory variables: Immigrants as share of employment</i>	(1) <i>Basic</i>	(2) <i>Controlling for R&D per worker</i>	(3) <i>Controlling for Computer Adoption</i>	(4) <i>Controlling for Trade</i>	(5) <i>Controlling for TFP growth based on sector composition (1960-2006)</i>
<i>OLS</i>	-0.98** (0.17)	-0.72** (0.17)	-0.91** (0.17)	-0.85** (0.19)	-0.94** (0.17)
<i>2SLS</i>	-1.10** (0.34)	-0.84** (0.14)	-1.01 (0.18)	-0.89** (0.18)	-1.11** (0.16)
$\hat{\beta}$ constructed with $\sigma=1.5$	-2.34** (0.45)	-2.04** (0.31)	-2.30** (0.37)	-1.90** (0.35)	-2.40** (0.35)
$\hat{\beta}$ constructed with $\sigma=2$	-0.59* (0.30)	-0.36** (0.10)	-0.48** (0.10)	-0.45** (0.14)	-0.60** (0.10)
<i>Explanatory variables:</i>	Task specialization channel: dependent variable $\hat{\beta}$				
Change in Employment due to Immigration	-1.12** (0.38)	-0.65** (0.20)	-1.02** (0.17)	-0.78** (0.25)	-0.96** (0.13)
Change in Communication- Manual specialization of natives	-0.06 (0.35)	-0.29 (0.44)	-0.11 (0.36)	-0.58 (0.43)	0.39 (0.52)
Observations	255	204	255	153	255

Note: Each cell in row 1 to 4 is the coefficient of the regression of $\hat{\beta}$ on the change in employment due to immigrants, estimated including time and state fixed effects. The baseline estimate (row 1) is OLS with TFP constructed using the assumption that $\sigma=1.75$. In the second row we use 2SLS with imputed immigrants and border distance interacted with decade dummies as instruments. In the third and fourth row the method of estimation is 2SLS and skill-biased productivity is constructed under the assumption that σ , the elasticity of substitution between more and less educated is 1.5 or 2. In the last two rows we report the coefficient of a regression of $\hat{\beta}$ simultaneously on the immigration rate and on the change in task-specialization of natives. The units of observations are 50 US states plus DC in each decade 1960-2000 plus 2000-2006. The errors in parenthesis are heteroskedasticity-robust and clustered by state. **= significant at 5%, *=significant at 10%.

Table 5:
Further Robustness checks of the main effects of net immigration

<i>Explanatory variable is immigration as percentage of initial employment;</i>	(1) <i>Basic</i>	(2) <i>Controlling for initial value of Dep. Var. ; No state effects</i>	(3) <i>Without border states (CA,AZ, NM, TX)</i>	(4) <i>Without the largest states (CA, NY, TX)</i>	(5) <i>1980-2006</i>	(6) <i>Controlling for growth of dep. Var. imputed from the sector composition</i>
<i>Dependent Variable:</i>						
\hat{N}	1.09** (0.45)	1.76** (0.43)	3.20** (0.87)	2.90** (1.10)	0.79** (0.27)	1.11** (0.47)
\hat{y}	0.88** (0.25)	0.60** (0.15)	2.41** (1.12)	2.77** (1.20)	0.64 (0.47)	0.75** (0.25)
\hat{A}	1.37** (0.27)	0.76** (0.18)	2.33** (1.16)	2.59* (1.39)	1.06** (0.39)	0.82** (0.15)
$\hat{\beta}$	-1.14** (0.15)	-0.44** (0.09)	-1.73** (0.63)	-1.05** (0.47)	-0.97** (0.16)	-1.11** (0.16)
<i>Observations</i>	255	255	235	240	153	255

Note: Each cell is the result of a separate regression. The explanatory variable is the net inflow of immigrant workers over an inter-census period as a percentage of the initial employment. The units of observations are US states (plus DC) in each decade 1960-2000 plus 2000-2006. The method of estimation is 2SLS with imputed immigrants and distance from border interacted with decade dummies as instruments. Each regression includes state and decade dummies, unless otherwise specified. The Errors in parenthesis are heteroskedasticity-robust and clustered by state. The calculated variables use the assumption that $\sigma=1.75$ and $\alpha=0.33$.

**= significant at 5%, *=significant at 10%.