THE EFFECT OF IMMIGRATION ON PRODUCTIVITY: EVIDENCE FROM U.S. STATES

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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 U.S. 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 also promoted the adoption of unskilled-efficient technologies.

I. Introduction

IMMIGRATION during the 1990s and the 2000s has significantly increased the presence of foreign-born workers in the United States. 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 (Borjas 2006; Card, 2001, 2007, 2009; Peri & Sparber, 2009), industrial specialization (Card & Lewis, 2007), and innovative capacity (Gauthier-Loiselle & 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 worked, 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.[1] 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: the distance from the Mexican border (interacted with decade dummies) that is correlated with the inflow of Mexicans and 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 past 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 effects of immigration on total factor productivity and the large, negative, and significant effects of immigration on the skill bias of productivity survive the instrumental variable strategy and the inclusion of these controls. However, we need 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 of 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, Doms, and Lewis (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 the choice of appropriate techniques in traditional sectors.

The rest of the paper is as follows. Section II introduces the production-function approach that we use to decompose the effects of immigration on inputs and productivity. Section III describes how each state-level variable is constructed and presents summary statistics for the period 1960 to 2006. Section IV 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

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

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respect to the effect of immigration on productivity. Section V provides some concluding remarks.

II. 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 rewrite equation (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 ratio.[4] Taking the logarithmic derivative over time (growth rate) of both sides of equation (3) and expressing them with a $\widehat{\ }$ we get[5]

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

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: (a) capital intensity $\widehat{\frac{K_{st}}{Y_{st}}}$, (b) total factor productivity $\widehat{A}_{st}$, (c) average hours worked $\widehat{x}_{st}$, and (d) 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}, grows only 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 or 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 equation (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 worker.[6] Clearly, identifying an exogenous inflow of immigrants and ensuring that immigration, and not

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

[3] In equation (1), if we carry the terms X_{st} and A_{st} inside the index $f(h_{st})$ and 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 (Katz & Murphy, 1992; Card & Lemieux, 2001), income distribution (Krusell et al. 2000), and technological growth (Acemoglu, 1998; Caselli & Coleman, 2006).

[4] In 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, Barro & Sala i Martin, 2004, p. 99).

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

[6] If immigration has some effect on productivity 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 & Peri, 2006; Gonzales & Ortega, 2009) confirms that this adjustment mechanism, through land prices and local price indices, is plausible.

other unobservable shocks, is driving the estimated elasticity is crucial to our goal. For these reasons, we discuss the instrumental variable strategy and the validity of the instruments at length and introduce controls for other long-run technological and specialization trends in section IV.

III. Construction of Variables and Summary Statistics

We consider as the units of analysis fifty U.S. states plus Washington, DC, 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 microdata samples (IPUMS) of the U.S. Decennial Census and the American Community Survey (Ruggles et al., 2008). For data on GSP, we use the series available from the U.S. Bureau of Economic Analysis (2008b). Finally, to calculate state physical capital, we use data from the National Economic Accounts, obtained from the U.S. Bureau of Economic Analysis (2008a). We now describe the construction of each variable in detail.

To construct employment and hours worked,[7] we use Census data.[8] Since they are all weighted samples, we use the variable personal weight (*PERWT*) to produce the aggregate statistics. We divide workers into 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 workers who are noncitizens or naturalized citizens.[9]

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 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 U.S. Bureau of Economic Analysis (BEA; 2008a). The BEA produces figures on GSP in current dollars. The currently available series covers the period 1963 to 2006. We use that series and convert it to constant 2000 dollars using the implicit price deflators for gross domestic product available from the BEA (2008b). Finally, we extend the series backward 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 use data relative only to 1960, 1970, 1980, 1990, 2000, and 2006 for the fifty states plus Washington, DC. 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 estimates only the stock of physical capital by industry at the national level.[10] Following Garofalo and Yamarik (2002), we use the national estimates of the capital stock over the period 1963 to 2006 for nineteen industries (listed in appendix 2 of the online supplement). 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 and 1970 to the period 1960 to 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 equation (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

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

[7] The details on variable definition, construction, and data are contained in the appendix in the online supplement.

[8] Specifically, we use the general 1% sample for Census 1960, the 1% State Sample, Form 1, for Census 1970, the 1% State Sample for Censuses 1980 and 1990, the 1% Census Sample for the year 2000, and the 1% sample of the American Community Survey (ACS) for the year 2006.

[9] To identify foreign born, we use the variable *CITIZEN* beginning in 1970 and *BPLD* in 1960.

[10] See the Appendix in the online supplement for a detailed description.

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

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

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

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

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 equations (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. Because there are several estimates of σ in the literature, most of which cluster between 1.5 and 2.0 (see Ciccone & 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 1 minus the share of income to labor (usually estimated around 0.67; Gollin, 2002).

The average growth rates by decade of all the variables described above are reported in table A1 in the online supplement. Some well-known tendencies are evident in the data. The progressive increase in the inflow of immigrants as a share of employment during the 1970s and again during the 1990s is noticeable. We also see the slowdown in total factor productivity during the 1970s and 1980s and the reacceleration 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, in particular during the 1970s and 1980s. The literature on wage dispersion across education groups (Katz & Murphy 1992; Autor, Katz, & Kearney, 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.

Table 1.—OLS Estimates of the Impact of Immigration on the Components of Gross State Product Growth

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

The explanatory variable is immigration as a percentage of initial employment. Each cell is the result of a separate regression. The explanatory variable is the net inflow of immigrant workers over an intercensus period as a percentage of the initial employment. The units of observations are U.S. 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 parentheses are heteroskedasticity robust and clustered by state. The calculated variables use the assumption that σ = 1.75 and α = 0.33. **Significant 5%, *10%.

IV. Estimates of the Effects of Immigrants

A. OLS Estimates

Our main empirical strategy is to estimate equations like equation (5) using, alternatively, the growth rate of different variables in lieu of the placeholder $\widehat{b_{st}}$. 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 fifty U.S. states (plus Washington, DC) using intercensus 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 $\left(\frac{\alpha}{1-\alpha}\right)\widehat{\frac{K_{st}}{Y_{st}}}$, total factor productivity $\widehat{A_{st}}$, average hours worked $\widehat{x_{st}}$, and the skill

[11] The exact procedure used to calculate individual hourly wages is described in the appendix in the online supplement.

TABLE 2.—2SLS ESTIMATES OF THE IMPACT OF IMMIGRATION ON THE COMPONENTS OF GROSS STATE PRODUCT GROWTH

Dependent Variable	(1) Basic 2SLS	(2) 1970–2006	(3) 1960–2000	(4) 2SLS, Including Lagged Dependent Variable	(5) Border Instrument Only
$\hat{N}$	1.09**	1.39**	1.23**	1.94**	1.11**
	(0.45)	(0.55)	(0.25)	(0.69)	(0.46)
$\hat{y}$	0.88**	0.71*	1.47**	0.22	1.03**
	(0.25)	(0.35)	(0.30)	(0.27)	(0.34)
Components of $\hat{y}$					
$\left(\frac{\alpha}{1-\alpha}\right)(\hat{K}-\hat{Y})$	−0.08	−0.13	0.27	−0.10	−0.08
	(0.13)	(0.13)	(0.23)	(0.14)	(0.09)
$\hat{A}$	1.37**	1.11**	0.97**	0.61**	1.15**
	(0.27)	(0.36)	(0.36)	(0.24)	(0.30)
$\hat{x}$	0.28**	0.17	0.61**	0.27**	0.24**
	(0.11)	(0.09)	(0.19)	(0.10)	(0.08)
$\hat{\phi}$	−0.26**	−0.29**	−0.14	−0.38**	−0.27**
	(0.07)	(0.08)	(0.11)	(0.08)	(0.07)
Components of $\hat{\phi}$					
$\hat{h}$	−1.16**	−0.90**	−1.58**	−0.89**	−1.14**
	(0.25)	(0.23)	(0.36)	(0.20)	(0.27)
$\hat{\beta}$	−1.14**	−0.84**	−1.74**	−0.49**	−1.08**
	(0.15)	(0.13)	(0.25)	(0.18)	(0.15)
First-stage F-test	17.42	7.48	17.99	17.42	13.11
Observations	255	204	204	204	255

The explanatory variable is immigration as a percentage of initial employment. Each cell is the result of a separate regression. The explanatory variable is the net inflow of immigrant workers over an intercensus period as a percentage of the initial employment. The units of observations are U.S. 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 parentheses are heteroskedasticity robust and clustered by state. The calculated variables use the assumption that $\sigma = 1.75$ and $\alpha = 0.33$. **Significant at 5%, *10%.

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 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 by OLS, including time and state fixed effects, accounts for common U.S. 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 1960s, and in column 3 we drop the 2000s) and whether including the lagged dependent variable in order to capture autocorrelation over time (column 4) or instrumenting immigrant employment changes with immigrant population changes (column 5) affects the estimates.

The estimates are quite stable across specifications, so we can simply comment on the general features of these correlations.[13] First, the elasticity of total employment to immigrants is always larger than 1 (sometimes as large as 2) and never significantly different from 1. 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 markets.[14] The estimates are often much larger than 1, potentially suggesting the existence of a demand-driven bias. Second, the coefficients in the second row show 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 find a 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 to 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.

B. *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 & Sparber, 2009), with a purely geographical instrument based on the distance from the border between Mexico and the United States. 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 ten different areas.[15] For each nationality of origin and each state, the total number of people of 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 United States. This allows us to impute the immigrant population from each nationality of origin in each state that we then

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

[13] The specification that produces estimates further 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).

[14] Given the way we constructed our variables, a coefficient of 1 on $\widehat{N_{st}}$ implies that one immigrant worker produced an increase in total employment of 1; hence, it produces no change in native employment.

[15] The 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.

add up across nationalities within a state to construct the imputed decennial growth of working-age population due to imputed immigrants. The variation of this measure across states depends only on the initial presence of immigrants (as of 1960) and their national composition and is independent of any subsequent state-specific economic factor. 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 U.S.-Mexico border (for Mexican immigrants) is the main point of entry to the United States. 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 (1960s, 1970s, 1980s, 1990s, and 2000–2006). 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.[16]

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 the 1%, 5%, or 10% confidence level.[17] 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 1 and never statistically different from 1. 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 autocorrelation 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 $\widehat{\phi}_{st}$ 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-decade.[18] 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 consistent 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 devote section IVC to testing their robustness to the inclusion of several controls. Before doing that, we remind readers that the 0 effect of immigration on capital intensity (capital-output ratio) in the long run (ten-year intervals) is consistent with the idea that U.S. 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.

C. *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 $(\widehat{A})$ and the negative and significant effect on the skill bias of technology $(\widehat{\beta})$. 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

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

[17] The test statistic, under the null hypothesis that none of the instruments appears 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 (five 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.

[18] We control for several of these state-specific factors in section IVC.

TABLE 3.—ESTIMATED IMPACT OF IMMIGRATION ON TOTAL FACTOR PRODUCTIVITY ($\hat{A}$)

Dependent Variable: $\hat{A}$	(1) Basic (1960–2006)	(2) Controlling for R&D per Worker (1970–2006)	(3) Controlling for Computer Adoption	(4) Controlling for Trade (1980–2006)	(5) Controlling for TFP Growth Based on Sector Composition (1960–2006)
OLS	0.80**	0.90**	0.70**	1.05**	0.50
	(0.39)	(0.37)	(0.38)	(0.53)	(0.35)
2SLS	1.37**	1.02**	0.88**	1.17**	0.82**
	(0.27)	(0.31)	(0.26)	(0.49)	(0.31)
2SLS	0.77*	0.73**	0.59*	0.94*	0.56*
TFP calculated as standard Solow residual ($\sigma = \infty$)	(0.41)	(0.35)	(0.29)	(0.54)	(0.30)
2SLS	1.72**	1.81**	1.70**	1.78**	1.53**
$\hat{A}$ *constructed with* $\sigma = 1.5$	(0.44)	(0.29)	(0.28)	(0.43)	(0.36)
2SLS	0.80*	0.75**	0.62**	0.94*	0.59*
$\hat{A}$ *constructed with* $\sigma = 2$	(0.41)	(0.34)	(0.29)	(0.53)	(0.31)
Explanatory variables			Task Specialization Channel: Dependent Variable $\hat{A}$		
Change in employment due to immigration	0.90	0.51	0.69	0.51	0.13
	(0.94)	(0.58)	(0.67)	(0.79)	(0.62)
Change in communication-manual specialization of natives	1.30*	1.63	2.70**	1.20	0.67
	(1.30)	(1.68)	(1.16)	(1.00)	(1.20)
Observations	255	204	255	153	255

Explanatory variables: Immigrants as a share of employment. Each cell in rows 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 a Solow residual without accounting for the imperfect substitution of the more and the less educated. In the fourth and fifth rows, total factor productivity is constructed under the assumption that σ, the elasticity of substitution between the more and the less educated, is 1.5 or 2. In the last two rows, we report the coefficient of a regression of A simultaneously on the immigration rate and the change in task specialization of less educated natives. The units of observations are fifty U.S. states plus DC in each decade 1960–2000 plus 2000–2006. The errors in parentheses are heteroskedasticity robust and clustered by state. **Significant at 5%, *10%.

TABLE 4.—ESTIMATED IMPACT OF IMMIGRATION ON SKILL BIAS ($\hat{\beta}$)

Dependent Variable: $\hat{\beta}$	(1) Basic	(2) Controlling for R&D per Worker	(3) Controlling for Computer Adoption	(4) Controlling for Trade	(5) Controlling for TFP Growth Based on Sector Composition (1960–2006)
OLS	−0.98**	−0.72**	−0.91**	−0.85**	−0.94**
	(0.17)	(0.17)	(0.17)	(0.19)	(0.17)
2SLS	−1.10**	−0.84**	−1.01	−0.89**	−1.11**
	(0.34)	(0.14)	(0.18)	(0.18)	(0.16)
$\hat{\beta}$ *constructed with* $\sigma = 1.5$	−2.34**	−2.04**	−2.30**	−1.90**	−2.40**
	(0.45)	(0.31)	(0.37)	(0.35)	(0.35)
$\hat{\beta}$ *constructed with* $\sigma = 2$	−0.59*	−0.36**	−0.48**	−0.45**	−0.60**
	(0.30)	(0.10)	(0.10)	(0.14)	(0.10)
Explanatory variables			Task Specialization Channel: Dependent Variable $\hat{\beta}$		
Change in employment due to immigration	−1.12**	−0.65**	−1.02**	−0.78**	−0.96**
	(0.38)	(0.20)	(0.17)	(0.25)	(0.13)
Change in communication-manual specialization of natives	−0.06	−0.29	−0.11	−0.58	0.39
	(0.35)	(0.44)	(0.36)	(0.43)	(0.52)
Observations	255	204	255	153	255

Explanatory variables: Immigrants as a share of employment. Each cell in rows 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 rows, the method of estimation is 2SLS, and skill-biased productivity is constructed under the assumption that σ, the elasticity of substitution between the more and the 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 the change in task specialization of natives. The units of observations are 50 U.S. states plus D.C. in each decade 1960–2000 plus 2000–2006. The errors in parentheses are heteroskedasticity robust and clustered by state. **Significant at 5%, *10%.

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 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 equation (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 2–5). 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 Solow[19] 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 discuss in section D.

Considering the different specifications (columns) in table 3 (and table 4), we first report the basic estimates obtained from a regression that controls only 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 1970s, 1980s, 1990s, and 2000s.[21] 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 important for our purposes, the inclusion of R&D as a control does not much affect 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 $\widehat{A}_{st}$ (not reported) is 2.10 (standard error 0.90), while on $\widehat{\beta}_{st}$, 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 $\widehat{A}_{st}$ 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 United States 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 effect.[24] We calculate exports as a share of GSP in 1987–1989 and attribute this value to the entire decade of the 1980s and then calculate the average export/GSP value by state in the 1990s 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 (s.e. = 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 fourteen sectors,[25] each weighted by the initial (1960) share of that sector in the state value added (BEA, 2009).[26]

[19] As it is described in Solow (1957).

[20] Formula (8) reduces to that of the Solow residual when $\sigma = \infty$.

[21] The data are from the National Science Foundation (1998) and include total (private and federal) funds for industrial R&D in constant 2000 U.S. dollars. The data are available every year for the period 1975 to 2006. We calculate the average yearly expenditure in a state between 1975 and 1979 and impute it over the 1970s. In the following periods we use the average yearly expenditure during the period.

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

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

[24] The data on exports of manufactured goods by state of origin are from the Origin of Movement data available from the U.S. 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.

[25] These sectors are agriculture, agricultural services, mining, construction, manufacturing of durable goods, manufacturing of nondurable goods, transportation, utilities, wholesale trade, retail trade, F.I.R.E., other services, and government.

[26] The data on sector-specific TFP are calculated using data on value added and capital stocks from BEA (2008b), deflated to 2000 US$ using the GDP and investment price deflator, respectively, and employment by industry also obtained from BEA (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.

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 (s.e. = 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.

D. *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 shows 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 & 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 more manual-intensive tasks to immigrants. 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 & 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 occupation, using the average of 52 ability variables collected in the U.S. Department of Labor's O*NET data set.[27] 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 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, when this task reallocation is controlled for, 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 productivity.[28] 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 at least part of the effect of immigrants on productivity comes from the reallocation of natives and immigrants across production tasks. Table 4 shows that the effect of controlling for task reallocation on the skill bias regression is much smaller (the coefficient is reduced by 5% to 10% in absolute value). Reallocation is likely to enhance overall efficiency. However, controlling for task reallocation, 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 effects[29] (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,

[27] For a list and classification of abilities into manual and communication skills, see table A1 of Peri and Sparber (2009).

[28] If we include only 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.

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

TABLE 5.—FURTHER ROBUSTNESS CHECKS OF THE MAIN EFFECTS OF NET IMMIGRATION

Dependent Variable	(1) Basic	(2) Controlling for Initial Value of Dependent Variable: No State Effects	(3) Without Border States (CA, AZ, NM, TX)	(4) Without the Largest States (CA, NY, TX)	(5) 1980–2006	(6) Controlling for Growth of Dependent Variable Imputed from the Sector Composition
$\hat{N}$	1.09**	1.76**	3.20**	2.90**	0.79**	1.11**
	(0.45)	(0.43)	(0.87)	(1.10)	(0.27)	(0.47)
$\hat{y}$	0.88**	0.60**	2.41**	2.77**	0.64	0.75**
	(0.25)	(0.15)	(1.12)	(1.20)	(0.47)	(0.25)
$\hat{A}$	1.37**	0.76**	2.33**	2.59*	1.06**	0.82**
	(0.27)	(0.18)	(1.16)	(1.39)	(0.39)	(0.15)
$\hat{\beta}$	−1.14**	−0.44**	−1.73**	−1.05**	−0.97**	−1.11**
	(0.15)	(0.09)	(0.63)	(0.47)	(0.16)	(0.16)
Observations	255	255	235	240	153	255

Explanatory variable is immigration as a percentage of initial employment. Each cell is the result of a separate regression. The explanatory variable is the net inflow of immigrant workers over an intercensus period as a percentage of the initial employment. The units of observations are U.S. 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 parentheses are heteroskedasticity robust and clustered by state. The calculated variables use the assumption that $\sigma = 1.75$ and $\alpha = 0.33$. **Significant at 5%, *10%.

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 the three most recent decades that 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 thirteen industries and then weighting those growth rates by the 1960 share of that industry in state value added[30] (specification 6) does not change the estimate much either.

V. Conclusion

This paper uses an aggregate accounting approach to analyze the relation between immigration and employment and the productivity of U.S. 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 them 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 or 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 a gain in overall efficiency. Preliminary empirical evidence supports this claim. The positive coefficient from the 2SLS estimates implies that the net inflow of immigrants, even those driven by their historical location and proximity to the border, is associated with significant productivity gains for the receiving states.

[30] The sector-based imputed growth of the dependent variables included in these regressions is 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 a control. In the regressions, of the second row, we include imputed GSP growth as a control. In the regressions of the third and fourth rows, we include the imputed TFP growth as a control.

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