The Effect of Immigration on Productivity: Evidence from US States

Giovanni Peri (UC Davis, CESifo and NBER)*

October 9, 2009

Abstract

Using the large variation in the inflow of immigrants across US states we analyze the impact of immigration on state employment, average hours worked, physical capital accumulation and, most importantly, total factor productivity and its skill bias. We use the location of a state relative to the Mexican border and to the main ports of entry, as well as the existence of communities of immigrants before 1960, as instruments. We find no evidence that immigrants crowded-out employment and hours worked by natives. At the same time we find robust evidence that they increased total factor productivity, on the one hand, while they decreased capital intensity and the skill-bias of production technologies, on the other. These results are robust to controlling for several other determinants of productivity that may vary with geography such as R&D spending, computer adoption, international competition in the form of exports and sector composition. Our results suggest that immigrants promoted efficient task specialization, thus increasing TFP and, at the same time, promoted the adoption of unskilled-biased technology as the theory of directed technologial change would predict. Combining these effects, an increase in employment in a US state of 1% due to immigrants produced an increase in income per worker of 0.5% in that state.

Key words: Immigration, Total factor productivity, Skill-biased technology, Capital accumulation.

JEL Codes: F22, J61, R11.

*Department of Economics UC Davis, One Shields Avenue, Davis CA 95616. email: gperi@ucdavis.edu. I thank Greg Wright for outstanding Research Assistance. I thank two anonymous referees for very helpful comments on a previous draft of this paper and participants in several seminars for suggestions. I gratefully acknowledge generous funding from the John D. and Catherine T. MacArthur Foundation.

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. In some states, such as California, one worker in three was foreign-born as of 2006, while in West Virginia only one in one hundred was. 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 take a more systematic approach and use a production-function representation of the economies of U.S. states to analyze the impact of immigration on the inputs to production (employment, average hours worked, average skill intensity, and physical capital), on productivity (total factor productivity and the skill-bias of productivity) and, through these, on income per worker. While a large literature has analyzed the effects of immigration on employment and hours worked[1] (and on wages, using labor market data) our contribution is to identify the impact of immigration on capital intensity, 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 likely to be related to immigration and much less to other determinants of productivity. These are the distance from the Mexican border and from the two main East-West ports of entry of immigrants (New York and Los Angeles), as well as the presence of immigrant communities prior to 1960. Interacted with decade dummies, these geographic variables provide variation that is a strong predictor of the immigrants' inflow, but a priory (as they are essentially geography-based) not with other productivity shocks. Second, in the instrumented regression of productivity on immigration rates we introduce proxies for many of the relevant causes of productivity growth in the last few decades. Treating these as potentially endogenous, and using the same geographical 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 and innovation, the adoption of computers, the openness to international trade as measured by the export intensity and the sector-composition of the state. Both the positive, significant and strong effect of immigration on total factor productivity and the large, negative and significant effect of immigration on the skill bias of productivity survive the inclusion of these controls and the instrumental variable strategy.

We then show that a measure of task-specialization of native workers induced by immigrants explains half to two thirds of the positive productivity effect, while the effect due to unskilled-biased technological adoption survives all controls and is compatible with a choice of directed technology at the state level as first pointed

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

out by Lewis (2005) and then by Beaudry, et al. (2008). These results, combined with a constant capital-labor ratio in production suggest that these productivity gains may arise due to the efficient allocation of skills to tasks, as immigrants are allocated to manual-intensive jobs, promoting competition and pushing natives to perform communication-intensive tasks more efficiently. Hence efficiency gains are likely to come from specialization, competition and choice of appropriate techniques in traditional sectors rather than from technological improvements in high tech sectors.

The rest of the paper is as follows: Section 2 introduces the production-function approach to accounting and decomposes the effects of immigration on inputs and productivity. Section 3 describes how each state-level variable is constructed and presents their behavior over 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

In order to analyze the impact of immigration on the total and average income of an economy and to decompose the channel through which immigrants may affect labor productivity, we adopt a production-function approach. Later we will use the predictions of a simple growth model for the long run balanced growth path of such an economy. We consider each U.S. state s in year t as producing a homogenous, perfectly tradeable output, using the following Cobb-Douglas production function:

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

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:

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

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. A value close to 1 implies that highly educated workers are much more productive than less educated ones, and an increase in β_{st} implies that the highly educated workers are becoming more productive relative to less educated workers.

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

Notice that in expression 1, if we carry the terms X_{st} and A_{st} inside the index $f(h_{st})$ and we call $A^H_{st} = \beta_{st} A_{st}$ and $A^L_{st} = (1 - \beta_{st})A_{st}$ we obtain a very common production function[3] used in several studies of aggregate labor markets (Katz and Murphy 1992, Peri and Sparber 2009), of income distribution (Krusell et al. 2000) and of technological growth (Acemoglu 1998, Caselli and Coleman 2007). 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 $\sigma > 0$ and A^H_{st} and A^L_{st} measure the productivity specific to more and less educated workers, respectively. In order to decompose the growth rate of output per worker using the production function and simple long-run assumptions, 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:

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

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, which is constant in the balanced growth path of any neoclassical model 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). We now take the logarithmic derivative (percentage change) of both sides of equation (3) over time and denote them with a$\widehat{\ }$(so that for any variable b, $d \ln b/dt = \widehat{b}$). The percentage change of total output and output per worker can therefore be expressed as follows:

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

Expression (4) is the basis of our empirical decomposition of the effects of immigration. It says that total output in a state increases as a consequence of increased employment ($\widehat{L_{st}}$) and of increased output per person ($\widehat{y_{st}}$). Output per person, in turn, increases due to the contribution of four factors: (i) the capital intensity of the economy, captured by the capital-output ratio $\widehat{\frac{K_{st}}{Y_{st}}}$, (ii) the total factor productivity $\widehat{A}_{st}$, (iii) the average hours worked $\widehat{x}_{st}$ and (iv) the productivity-weighted skill-intensity index measured by $\widehat{\phi}_{st}$. Such a decomposition is convenient for several reasons. First, 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 sometimes treated as, would only increase $\widehat{N_{st}}$ with no effect in the long run on any other variable nor on y_{st}. However, immigration can be much 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

[3] It can be written as: $Y_{st} = K^{\alpha}_{st} \left[\left(A^H_{st} H_{st}\right)^{\frac{\sigma-1}{\sigma}} + \left(A^L_{st} L_{st}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}(1-\alpha)}$

capital adjustment can produce decreases in productivity and capital intensity. Moreover, if the transition dynamics to the new balanced growth path are slow, capital may take a long time to adjust and the term $\frac{K_{st}}{Y_{st}}$ may be below its steady state for a while. With our approach we can analyze the impact of immigration on each of the five terms on the right hand side of (4). A second interesting feature of this approach is that by analyzing the impact on employment ($\widehat{N_{st}}$) and average hours worked ($\widehat{x}_{st}$) we can confirm or revise the existing evidence (from labor market analysis) that immigration did not crowd out natives but instead increased total employment leaving average hours worked unchanged[4]. In analyzing the impact on $\widehat{\phi}_{st}$ we can also verify whether immigration has increased the share of unskilled workers and what average effect this had on productivity. Finally, we can focus on more novel channels: did immigration affect capital intensity $\widehat{\frac{K_{st}}{Y_{st}}}$ or total factor productivity $\widehat{A}_{st}$? Combining these channels we will be able to understand if immigration leads to a simple employment increase, possibly biased towards the less educated, or if it has long-run effects on the structure of the receiving economies. Moreover, since we are also able to identify the separate effects on A_{st} and β_{st} we can identify what type of productivity gains (whether skilled or unskilled-biased) or losses have been produced by immigration.

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 states (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:

$$\widehat{b}_{st} = \alpha_t + \eta_b \frac{\Delta N_{st}^F}{N_{st}} + \varepsilon_{st} \tag{5}$$

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 highly educated workers 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 α_t and ε_{st} are, respectively, year fixed effects and zero-mean random shocks.

These regressions produce estimates within a common framework that can then be aggregated to obtain the effect on total income and on income per worker, thus measuring the aggregate and per capita gains (or losses) from immigration and the importance of each channel. Clearly, identifying an exogenous inflow of immigrants and ensuring that immigration, and not other unobservable, correlated 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

[4] We take as reference the labor market estimates of Card (2001), Card (2007) and Card (2009) that do not find any significant negative crowding out effect of immigrats on native employment across US cities.

the instruments at length and will introduce controls for other long-run technological and specialization trends in section 4.

Before implementing our empirical analysis, let us specify an important theoretical underpinning of it. If each state has a production structure as described above and if immigration has some effect on productivity and/or capital intensity (say positive, as we will find below) 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 due to productivity differences, these are, however, absorbed by corresponding differences in the average price index across states, which is driven by differences in the prices of housing or fixed amenities. Hence, a differential increase in income per worker in state s relative to state r due to immigration $(\widehat{y_{st}} - \widehat{y_{rt}})$ is accompanied by equivalent growth in the price index of state s and r as the result of changes in housing, land and fixed-amenities prices. Formally this implies that $\widehat{p_{st}} - \widehat{p_{rt}} = \widehat{y_{st}} - \widehat{y_{rt}}$ and thus real income differences are unchanged $(\widehat{y_{st}} - \widehat{p_{st}} = \widehat{y_{rt}} - \widehat{p_{rt}})$ for any couple of states. This is compatible with an equilibrium where workers are mobile. Since we measure output and capital at common US prices (not adjusted for local cost of living) our analysis allows us to study productivity and wage differences across states driven by immigrants. The large literature that documents a strong positive effect of immigration on housing prices[5] confirms that this adjustment mechanism, through land prices and local price indices, is plausible.

3 Data and Construction of Variables

3.1 Variables Measured Directly

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 worked[6] 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

[5] For instance Saiz (2003, 2007), Ottaviano and Peri (2006), Gonzales and Ortega (2009).
[6] The details on variable definiiton, construction and data are in the Appendix A.

for year 2000 and the 1% sample of the American Community Survey (ACS) for the year 2006. Since they are all weighted samples we use the variable "personal weight" to produce the average and aggregate statistics. To produce measures of hours worked (or employment) by state and level of education we select the following sample. First, we include people age 17 and older in the census year (corresponding to 16 and older the previous year[7]) not living in group quarters who worked at least one week in the previous year, received positive wage income and were not self-employed. We then select only workers with work experience of at least one year and less than or equal to forty years[8]. 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) using the variable EDUCREC which classifies levels of education consistently across censuses and ACS data. The "foreign-born" status used to identify native and immigrant workers is given to those workers who are non-citizens or are naturalized citizens (using the variable "CITIZEN" beginning in 1970 and "BPLD" in 1960).

The hours of labor supplied by each worker are calculated by multiplying hours worked in a week by weeks worked in a year and individual hours are multiplied by the individual weight (PERWT) and aggregated within each education-state group. This measure of hours worked by education group and state is the basic measure of labor supply. We call H_{st}^{D} and H_{st}^{F} the hours worked, respectively, of domestic (native) and foreign highly educated workers in state s and year t so that $H_{st} = H_{st}^{D} + H_{st}^{F}$ is the total of hours worked by highly educated workers in state s and year t. Similarly, we call L_{st}^{D} and L_{st}^{F} the hours worked, respectively, by domestic (native) and foreign less educated workers in state s and year t so that $L_{st} = L_{st}^{D} + L_{st}^{F}$ is the total of hours worked by less educated workers in state s and year t. Finally, 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; $x_{st} = X_{st} /\!/ N_{st}$ measures the average hours worked in the economy in state s in year t; and the variable $h_{st} = H_{st}/X_{st}$ measures the share of hours worked by the highly educated 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 by combining data on local labor income, local business taxes and local capital income by industry and state and complementing these with value added data from the Economic Census. 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

[7] Sixteen years of age is the cut-off chosen by the Bureau of Labor Statistics for those people who are defined as "working age".

[8] Experience is calculated using the variable "AGE" and with the assumption that people without a high school degree enter the labor force at age 17, people with a high school degree enter at 19, people with some college enter at 21 and people with a college degree enter at 23.

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 level[9]. Following Garofalo and Yamarik (2002) we use the national estimates of the capital stock over the period 1963-2006 for 19 industries (listed in Appendix C). We then distribute the national capital stock in a year for each industry across states in proportion 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}.

3.2 Variables calculated indirectly

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:

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

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

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

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

[9] See Appendix B for details.

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

The only new variables required to calculate β_{st} and A_{st}, besides those described in section 3.1 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 (calculated from the same sample as the one used for hours worked) by state and year, first separately for individuals with some college education or more, w_{st}^{H}, and then for those with high school education or less, w_{st}^{L}[10]. 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. As there are several estimates of this value in the literature, most of which cluster between 1.5 and 2.0 (see Ciccone and Peri 2006 for a recent estimate and a summary 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.

3.3 Summary statistics and trends

The average growth rates, by decade, of all the variables considered in the analysis–those measured directly ($\frac{\Delta N_{st}^{F}}{N_{st}}, \widehat{N_{st}}, \widehat{y}_{st}, \widehat{\frac{K_{st}}{Y_{st}}}, \widehat{x}_{st}$ and $\widehat{h}_{st}$), as well as those calculated indirectly ($\widehat{A}_{st}, \widehat{\beta}_{st}$)–are reported in Table A1 of the 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 growth of income per worker and, correspondingly, of 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.

Figures 2, 3 and 4 also illustrate the average and state-specific behavior of income per worker, capital per worker and TFP, respectively, all in logarithmic terms. Besides confirming the average tendencies of those variables, the figures also show a moderate tendency of income per worker and TFP to converge across states (the vertical spread between top and bottom states tends to contract over time) indicating continued technological convergence over the period. Figure 4, capital per worker, shows less convergence than the other two and some states with particularly large mining and oil sectors stand out as outliers. Finally, Figures 5 and 6 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) has emphasized this finding, attributing it to directed skill-biased technological change. Also, these two variables seem to exhibit a clear tendency towards cross-state convergence over the period. Reassured by the behavior of our measured and constructed variables, which match

[10] The exact procedure used to calculate individual hourly wages is described in A.

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 $\widehat{b}_{st}$. The dependent variables used in the regressions are shown in the first column of Tables 1 through 6, 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 fixed effects, weights each cell by the total employment in it, and reports the heteroskedasticity-robust standard errors clustered by state. 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-intensity index $\widehat{\phi}_{st}$. Those four effects add up to the total effect on $\widehat{y_{st}}$. 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 $\widehat{\beta}_{st}$. Estimating the effect via OLS and without any further controls[11], but with common time effects, leaves the estimates subject to endogeneity and omitted variable issues. We propose an estimation strategy that addresses those issues in the next sections.

In Table 1 we provide some evidence of stable and strong correlations between immigration and some of the relevant growth rates, while including some simple controls and robustness checks. In particular, we 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 autocorrelation over time (column 4) or instrumenting employment changes due to immigrants with the population changes caused by them (arguably a measure that is less affected by labor market conditions) affects the estimates.

The estimates are quite stable and robust across specifications 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 and never significantly different from one. This confirms the existing evidence (Card 2001, Card 2005, Cortes 2008, Ottaviano and Peri 2006) that there is no crowding-out of native employment by immigrants in local labor markets[12]. The estimates are often larger than one, suggesting the existence of a demand-driven bias.

[11] Estimating the regressions for the components of $\widehat{y_{st}}$ simultaneously in a seemigly unrelated least square regresion (SUR) that accounts for correlation between the errors, produces almost identical elasicity estimates.

[12] Given 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.

Second, there is a consistent positive and significant correlation between income per worker and immigration. This positive correlation results from the combination of a positive correlation of immigration with total factor productivity, with an elasticity in the proximity of 1.25, and a negative correlation between immigration and capital intensity, with an elasticity around -0.5. The positive effect of immigrants on hours worked (+0.12/0.13) and the negative effect on the skill index $\widehat{\phi}_{st}$ (-0.15/-0.19) compensate for each other in terms of income per worker.

Finally, we also find a very significant and robust negative correlation between the immigration rate in employment and both the share of more educated workers as well as the skill-bias of technology, both with an elasticity not far from -0.7. States with larger than average inflows of immigrants over the period 1960-2006 were therefore associated with a 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 capital and the skill intensity of production grew at a slower rate. To look more closely at these effects we begin addressing the endogeneity and omitted variable bias of the OLS estimates using an instrumental variable technique.

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 in several other studies (including Card 2009 and Peri and Sparber 2009), with a purely geographical instrument based on the distance from the main points of entry of immigrants into 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[13] from 10 different areas: Mexico, Rest of Latin America, Canada-Australia-New Zealand, Western Europe, Eastern Europe and Russia, China, India, Rest of Asia, Africa and Others. Let us call these ten the "nationality of origin" of the immigrants. For each nationality of origin n and each state i the total number of people in working age (16-65) in Census 1960 is $Pop_{n,i,1960.}$ For each nationality of origin we also calculate the rate of growth of the total working age population in the U.S., namely: $g_{n,1960-t} = (Pop_{n,t.} - Pop_{n,1960})/Pop_{n,i,1960}$. This allows us to impute the immigrant population from each nationality of origin in each state, by applying the national growth rate to the 1960 population from that nationality in each state. Hence the "imputed" immigrant population from nationality n in state i would be $\widehat{Pop}_{n,i,t} = Pop_{n,i,1960.} * (1 + g_{n,1960-t})$. Adding up across nationalities we have the total imputed population of immigrants in each state and year: $\widehat{Pop}_{Fi,t} = \sum_n \widehat{Pop}_{n,i,t}$. Finally, we construct the imputed decennial growth of working age population due to immigration as $\left(\widehat{Pop}_{Fi,t+10} - \widehat{Pop}_{Fi,t}\right)/(\widehat{Pop}_{Fi,t} + Pop_{U.S.,i,t})$ where $Pop_{U.S.,i,t}$ is the actual native population of working age in state i and year t. We use this measure as an instrument for the growth in employment due to immigrants

[13] Using the variable BPLD for 1960 and BPLD and CITIZEN for 1970 and later.

in each state and decade, $\frac{\Delta N^F_{st}}{N_{st}}$.

The US-Mexico border (for Mexican immigrants) and Los Angeles and New York (for other travelers) are the main points of entry to the U.S. The distance of each state's center of gravity from the Border, New York and Los Angeles is calculated as follows. First, we obtain data on the geodesic coordinates of each state's population center of gravity from the 2000 Census as well as for 12 sections of the U.S.- Mexican border, covering its entire length, and for New York, Los Angeles and Miami. We then use the formula for geodesic distance to calculate the distance (in thousands of kilometers) between each state's center of gravity and the relevant points of entry. 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 immigration and the distance from Los Angeles had a larger impact on immigrant inflows in periods of large immigration from China and Asia.

The imputed immigrants and geographic instruments have strong power. Their F-test in the samples used vary between 36 and 44 when used jointly (see the second to last row in Table 2). Even the geographic instruments by themselves have significant power (F-test of 25, as reported in the last column of Table 2). Moreover, the instruments, when used jointly, pass the test of overidentifying restrictions and one cannot reject the assumption of exogeneity of instruments at 5% confidence level[14]. 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 geographic instruments (specification 5) we obtain a very consistent picture. First, the impact on total employment is now estimated to be close to one and never statistically different from one. The difference between the OLS and the 2SLS estimates confirms the idea that some reverse causality may bias the OLS estimates up. Similarly, the effect on the growth of income per worker is lower than in the OLS case and between 0.4 and 0.5, still statistically significant in all specifications. Decomposing this effect one sees that the positive elasticity results from the combination of a positive effect on TFP with a negative effect of around -0.5 on capital intensity.

In the estimates in Table 2 the negative effect of immigration on the skill index $\widehat{\phi}_{st}$ is not fully balanced by the positive effect on hours worked and so those two terms contribute negatively 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. Interpreting the coefficient as causal, which would be the case if the instruments are uncorrelated with any economic factor affecting productivity and growth in a state-decade, the analysis reveals three effects of immigration not clearly measured before and confirms two well-known effects. First, immigration mechanically increases employment

[14] The 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 (15 in our case). The test statistics equals 7.65. The corresponding value for the relevant Chi-square distribution, with 15 degrees of freedom, is 0.07, and hence the null hypothesis level stands at 5% confidence. See Wolrdige (2002) for the details of the test.

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 less capital intensive and more unskilled-intensive (both effects were suggested by Lewis 2005 and are consistent with the idea of directed technological choice) but it also increases overall factor-neutral productivity.

The most remarkable and new estimated effects 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 4.4 to testing their robustness to the inclusion of several controls. Before doing that, however, let us also analyze the impact of immigrants on capital intensity. Capital intensity, measured as the capital-output ratio, may decrease either because the capital stock does not respond to immigration, because it responds less than employment, or because, in spite of a full response to employment, the capital-labor ratio does not increase as TFP increases. We decompose the decrease in the next section in order to isolate these three effects and we find that the decrease in capital-output is due to an increase in TFP vis-a-vis a constant capital-labor ratio.

4.3 A closer look at physical capital

Table 3 analyzes the response of the growth rate of the capital stock, $\widehat{K}_{st}$, of the capital-labor ratio, $\widehat{K}_{st} - \widehat{N}_{st}$ and of the standardized capital-output ratio $\left(\frac{\alpha}{1-\alpha}\right)\widehat{\frac{K_{st}}{Y_{st}}}$ to immigration as a share of employment. We report the OLS estimates (specifications 1 to 3) and 2SLS estimates (specifications 4 to 6) using all instruments. We allow for samples that omit the initial decade (specifications 2 and 4) or the last one (specifications 3 and 6). In all the regressions we include the capital-labor ratio of the state at the beginning of the decade to control for the potential tendency of capital intensity to convergence across states, and we report heteroskedasticity-robust standard errors, clustered by state. The estimates, especially those using 2SLS, show that within the decade immigration produced a one-for-one response of capital so that the capital-labor ratio in states receiving more immigrants did not decline at all as a result. The inflow of immigrants stimulated a corresponding increase in investment that left the capital-labor ratio basically unchanged. However, because of the productivity increase, output is growing faster than employment and, when measured in terms of the capital-output ratio, the economy is adopting technologies that appear less capital intensive. The reduction in capital intensity is not due to incomplete adjustment of capital to labor but to the disproportionate increase in output. Rather than being the result of a slow adjustment of the capital stock this phenomenon seems more likely due to a change in the capital intensity of the production techniques adopted, possibly associated with the chosen technology or productive organization. The corresponding reduction in the skill-intensity of the productivity (the effect on β) may be associated with this phenomenon. The model in Krusell et al. (2001) in which skill-biased technologies are explicitly linked to the intensity of equipment/capital in production may provide a joint explanation for the two phenomena: immigrants stimulate the choice of techniques toward those that more efficiently use less educated workers and are less capital intensive.

4.4 The Effects on Productivity and Skill-Bias

The most remarkable and novel effects estimated in Table 2 are the positive, large and significant effect of immigration on total factor productivity ($\widehat{A}$) and the negative, large 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 always very significant. The concern is that the geographic instruments used in the 2SLS estimation, while certainly affecting the immigration rates and certainly exogenous with respect to technological changes, may be correlated with other features that have affected productivity growth and its skill-intensity. The geographic location of a state, for instance, may be correlated for climatic reasons with its amenities, or also with its sector composition (think of agriculture and mining) which may affect its access to international and national markets and therefore the location of highly educated workers along with the adoption and diffusion of technologies. For these reasons we include in the regression several variables that are aimed at capturing the independent influence of these factors 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 geographic and imputed-immigrant instruments to predict them. While the instruments are not very powerful in predicting the controls, what we care about is that they maintain power in predicting immigration rates and that the estimated effect of immigration remains significant.

The coefficient on the control variables is often estimated imprecisely (and we do not report them in Tables 4 and 5); 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 geography-based instruments that is orthogonal to the controlled factor (and hence independent from it) to predict the immigration rate and its effect on productivity. We include the controls one at the time, since including them all together reduces the power of the instrument so drastically that we obtain very large standard errors. Table 4 shows the estimated coefficients on the immigration rates in regressions based on (5), using $\widehat{A}_{st}$ as the dependent variable. Table 5 shows the coefficients of a similar regression with $\widehat{\beta}_{st}$ as the dependent variable. Proceeding from top to bottom, Tables 4 and 5 show estimates obtained using OLS estimation methods (first row) or 2SLS estimation methods (rows 2 to 4). 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). The last two rows of Tables 4 and 5 report results from a specification that we will discuss in section 4.5.

Considering the different specifications (columns) in Table 4 (which correspond to those in Table 5), we first report the basic estimates obtained from a regression that only controls for time 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 and 90's. The data are from the National Science Foundation (1998) and include total (private and federal) funds for industrial R&D in constant 1990 US dollars[15]. We obtain the variable by dividing the aggregate state data by state employment. The estimated effect of the R&D variable on TFP changes (not reported and corresponding to the specification in the basic 2SLS in the second row) 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. Due to the low power of the instruments in predicting it, however, the estimated standard errors are large and the estimates are not significant. More importantly for our purposes, the inclusion of R&D as a control (and the shortening of the sample to 1970-2000) does not affect much the estimated effect of immigration on TFP (with an elasticity of 1.15 in the basic specification) and on the skill-bias (an elasticity of -0.94).

The second column of Tables 4 and 5 introduces computer use as a control. The adoption of computer technology is a major technological innovation leading to increased productivity, especially of the highly educated, and since its diffusion varied by sector and location we can control for it. To do this, we introduce the share of workers in each state that use a computer at work to the regression. The 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 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 in 1980, 1990 and 2000 for each state. We include this control in specification (3). 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)[16]. As expected, computer adoption has a positive and skill-biased effect on productivity across states. More interesting for us, however, is that the effect of immigration on $\widehat{A}_{st}$ is still large and significant (but reduced by 30% to an elasticity of 0.72) and the effect on the skill-bias is essentially unchanged in its magnitude (0.90) and significance (standard error equal to 0.13). While the adoption of computers may involve the reorganization of production in a way that is similar to the task specialization that occurs between natives and immigrants (see the next section), the productivity gains from geography-driven migration flows are robust to the inclusion of the computer adoption variable.

The third control, introduced in specification (4), is also a very important one. The geographic location of an economy is a very important determinant of its trade with the rest of the world. Being close to a major port, to the coast, to navigable rivers and the distance from other countries all affect trade costs and hence trade

[15] The data are available every year for the period 1975-1998. We calculate the average yearly expenditure in a state between 1975 and 1979 and we impute it over the whole 70's decade and the average over 1991-1998 is used for the 90's decade.

[16] In both cases we report the coefficients from the basic 2SLS specification in the second row.

volumes. Moreover, during the decades between 1960 and 2009 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 effect. The 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. 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. The downside is that we have to limit our analysis to the 80's, 90's and 2000-2006. The coefficient obtained for the effect of trade on productivity is negative (-0.36) and significant (standard error 0.13) while the effect on the skill-bias is not significant. While such a negative effect is somewhat surprising, it is worth noting that if we only include trade as an explanatory variable in the TFP regression (instrumented with the geographic variables) its effect is estimated to be positive (+0.30), although not significant (standard error 0.70). When included as a control (as in column 4) its effect become negative, while immigration maintains a positive and very significant, in fact enhanced (+1.51), effect on productivity (Table 4), with an unchanged effect on the productivity bias (-1.04). These results imply that the geographic openness of a state seems to have affected productivity positively, but the effect worked through immigration and not trade. This is an interesting finding, as the many papers studying the effect of trade on growth across countries (e.g., Frankel and Romer 2003) do not control for migration flows.

Finally, the last column of Tables 4 and 5 introduces a control that accounts for the wage growth in each state, according to its sector-composition. In particular, we construct a proxy for sector-driven productivity growth by averaging the growth rate of the average wage in each of 13 sectors (defined as the 2-digit definition of the variable IND1990 in the IPUMS), each weighted by the initial (1960) share of that sector in state employment. This control accounts for the fact that different states had different sector structures in 1960 and this might be correlated with geography and it affect on productivity growth. The inclusion of this variable (whose coefficient on TFP is positive and very significant) does not modify much the effect of immigration on $\widehat{A}_{st}$ and on $\widehat{\beta}_{st}$. In summary, the (unskilled-biased) productivity effect of immigrants is quite robust to the inclusion of several controls. This, together with the null effect on native employment, implies that across the analyzed time-horizon (ten year changes) immigration had a positive effect on the total wages of natives.

4.5 The Efficient Task-Specialization Hypothesis

There are two mechanisms proposed and studied in the previous literature that 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. Combining these findings with the theory of "directed technological change" or "appropriate technological adoption" (Acemoglu 2002) one can infer that the availability of unskilled workers pushes firms to adopt technologies that are more efficient and intensive in the use of unskilled workers. 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 4 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 O*NET dataset. Then we calculate the average of the ratio of these two task intensities for native workers in each state s and year t, C_{st}/M_{st}. The percentage change in this variable 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 exactly what we observe in the last two rows of Figure 4, where we report the coefficients on the immigration variable and on the specialization change, estimated by 2SLS and also including (in specifications 2 to 5) the other controls.

Two important patterns emerge. First, the estimated coefficient on the change in specialization is positive and mostly significant–in other words, the specialization change instrumented by geography has a positive effect on productivity. Second, the coefficient on the immigration variable, while still positive, is reduced significantly, often to half of its original estimate (without a control for specialization). It also loses its significance in three 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 a sign that a large part of the positive productivity effect may actually go through the efficient re-allocation of natives and immigrants across production tasks. The effect of controlling for task re-allocation in the skill-bias regression is much smaller. This is expected, as reallocation is likely to enhance overall efficiency. However, even controlling for task re-allocation, states with a large inflow of immigrants are likely to choose relatively unskilled-intensive techniques.

4.6 Robustness of the main estimated effects

The overall picture emerging from the empirical analysis is clear. Confirming the results of several articles on the labor market effect of immigrants we find that they have a one-for-one impact on total employment, with no evidence of crowding out of natives. More interestingly, we find that immigrants had a significant, positive effect on the total factor productivity of states, with a significant pro-unskilled bias. The productivity effect (combined with other smaller effects on capital intensity, skills and hours worked) drives a positive and significant effect of immigration on GSP per worker. In this section we check whether these effects (on $\widehat{N_{st}}, \widehat{y}_{st}, \widehat{A}_{st}$ and $\widehat{\beta}_{st}$) are all robust to further controls and sample restrictions. Table 6 presents the estimates of the elasticity of the variables to immigrants when estimated in 2SLS, allowing for different robustness checks. 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. Including the initial value of the dependent variable to account for convergence (column 2 of Table 6) does not change any qualitative result; in fact, it increases the estimated positive impact of immigration on employment, GSP per worker and productivity.

If we eliminate the border states (with Mexico) in specification (3) the explanatory power of the instruments is reduced, which is evident in the larger standard errors. However, while the employment effect is estimated to be much smaller, though very imprecise, all the other effects (notably on TFP and GSP per worker) are positive, larger than in the basic sample, and still very significant. The standard errors and estimates also increase when we eliminate the largest state economies (California, Texas and New York), which are also the largest receivers of immigrants. Overall, while a large part of the variation in the instrument is between border or coastal states and the rest, so that dropping them reduces the precision, the positive elasticity of productivity and GSP per worker to immigrants may be even larger in non-coastal, non-border states. This suggests that possibly the larger efficiency gains per immigrant from specialization are realized when immigrants are a small group and access highly manual-intensive occupations in services, construction, agriculture and manufacturing. As they become a larger fraction of the labor force they access occupations where they do not have such a large relative advantage and the overall efficiency gain per immigrant decreases. Finally, restricting the sample to only the three most recent decades, which experienced by far the largest aggregate inflow of immigrants, and including 4 regional dummies (West, South, Midwest and East) does not change the estimates much. Even when estimated within regions the inflow of immigrants is found to have had a significant, positive effect on productivity and GSP per worker.

4.7 Effects on wages

To make a final check of the consistency of our results with those found in the labor literature (which mostly analyzes the wage impact of immigrants), from our estimates we can obtain the impact of immigration on the wages of more and less educated workers. If we define the hourly wages of more and less skilled workers as the marginal productivity of H_{st} and L_{st}, and then manipulate the expression, collect common terms and calculate the rates of change, we obtain the following two decompositions that help us attribute the percentage change in wages to the factors that we have just studied:

$$\widehat{w_{st}^H} = \left(\frac{\alpha}{1-\alpha}\right)\frac{\widehat{K_{st}}}{Y_{st}} + \widehat{A}_{st} + \frac{1}{\sigma}\left(\widehat{\phi_{st}} - \widehat{h_{st}}\right) + \frac{\sigma-1}{\sigma}\widehat{\beta_{st}} \tag{9}$$

$$\widehat{w_{st}^L} = \left(\frac{\alpha}{1-\alpha}\right)\frac{\widehat{K_{st}}}{Y_{st}} + \widehat{A}_{st} + \frac{1}{\sigma}\left(\widehat{\phi_{st}} + \frac{h_{st}}{1-h_{st}}\widehat{h_{st}}\right) - \frac{\sigma-1}{\sigma}\widehat{\beta_{st}}\frac{\beta_{st}}{1-\beta_{st}} \tag{10}$$

The first two terms on the right hand side of (9) and (10) are common to both formulas and imply that increases in the capital-labor ratio and in the total factor productivity of the economy increase the marginal productivity of all workers and increase the hourly salaries of both types of workers. In contrast, the remaining terms show that an increase in the share of highly educated workers $\widehat{h_{st}}$ or in their relative productivity $\widehat{\beta_{st}}$ has differential effects on more and less skilled workers. The hourly wages of highly educated workers benefit from a *decrease* in the share h_{st} and from an increase in β_{st}, while the hourly wages of less educated workers benefit from an increase in h_{st} and from a decrease in β_{st}. Using the estimates from Table 2, Column 1, the effect of an inflow of immigrants equal to 0.50% of initial employment (which was roughly the yearly inflow during the period 1990-2006) on the wages of more educated workers is equal to +0.36%[17]. On the other hand, still using the estimates from Table 2, Column 1 and the formula in (10), and using as initial values of h_{st} and β_{st} their values in 1990, we obtain the result that the same increase in immigrants (equal to 0.50% of current employment) produces a 0.04% increase in the wages of less educated workers[18]. These values are in line with most of the literature on the labor market effects of immigrants that finds a somewhat positive effect of immigration on the highly skilled (e.g., Card 2009, Ottaviano and Peri 2008) and an effect close to zero on the wages of the less skilled (Card 2001, 2009). Our decomposition emphasizes that the supply effect of immigrants on less educated workers is balanced by the unskilled-biased productivity effect, so that the result is a very small wage effect on less educated workers. On the other hand, the TFP and supply effects are large enough for highly educated workers so that, in spite of the unskilled-biased impact of immigrants, the overall effect of immigration on their wages is positive.

[17] The calculations involve simply substituting the terms from Table 2 into (9) as follows: $1.06 - 0.47 + (1/1.75) * (-0.21 + 1.08) - (0.75/1.75) * 0.85$ and then multiplying by 0.5.

[18] These calculations simply involve substituting the terms from Table 2 into 10: $1.06 - 0.47 + (1/1.75) * (-0.21 - (1.22) * (1.08)) + 0.43 * 0.85 * 1$ and then multiplying by 0.5.

5 Conclusions

This paper uses an aggregate accounting approach to estimate the effect of immigration on productivity, capital intensity and the skill-bias of US state economies. We consider the variation in immigrant location due to geography (as an instrument) in order to isolate the causal effect of immigration on these variables. We also control for several other determinants of productivity that vary across states and are possibly related to their location. We present three main findings, two of which are quite new in this literature. First, we confirm that immigrants do not crowd-out employment of (or hours worked by) natives but simply add to total employment. Second, we find that they increase total factor productivity significantly and, third, that such efficiency gains are unskilled-biased–larger, that is, for less educated workers. We check that these effects are robust to including several control variables (such as R&D spending, technological adoption, sector composition or openness to international trade) and that they are not explained by productivity convergence across states or driven only 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. In conclusion, we also check that these findings are in line with the analysis of the wage effect of immigrants on less educated natives, which is close to 0, and on highly educated natives, which is positive.

References

Acemoglu„ Daron (1998). "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality", *Quarterly Journal of Economics* 113, 1055-1090.

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

Barro, Robert J. and Xavier Sala-i-Martin (2004). "Economic Growth" Second Edition, MIT Press, Cambridge Massachusetts,

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

Card, David (2001). "Immigrant Inflows, Native Outflows, and the Local labor Market Impacts of Higher Immigration" *Journal of Labor Economics*, XIX (2001), 22-64.

Card, David (2005) "Is The New Immigration Really So Bad?," *Economic Journal*, 2005, Volume 115, pp.300.323.

Card, David (2007) "How Immigrants Affects U.S. Cities" CReAM Discussion paper No. 11/07.

Card, David (2009). "Immigration and Inequality" *American Economic Review, Papers and Proceedings,* 99:2, 1-21.

Card, David and Ethan Lewis (2007) "The Diffusion of Mexican Immigrants During the 1990s: Explanations and Impacts" in *Mexican Immigration to the United States*, George J. Borjas editor, The University of Chicago Press, Chicago, London, 2007.

Caselli, Francesco and John W. Coleman (2006) "The World Technology Frontier", *American Economic Review*, 96:3, 499-522.

Ciccone, Antonio and Giovanni Peri (2005) "Long-Run Substitutability between More and Less Educated Workers: Evidence from U.S. States 1950-1990", *Review of Economics and Statistics* 87:4, 652-663.

Frankel, Jeffrey and David Romer (1999) "Does Trade Cause growth?" *Quarterly Journal of Economics*, Vol 83, 3. pp. 379-399.

Garofalo, Gasper A. and Steven Yamarik, (2002). "Regional Convergence: Evidence From A New State-By-State Capital Stock Series," *The Review of Economics and Statistics*, MIT Press, vol. 84(2), pp. 316-323.

Gauthier-Loiselle, Marjolaine and Jennifer Hunt (2008) "How Much Does Immigration Boost Innovation?" NBER Working Paper # 14312 Cambridge, Ma.

Gonzales, Libertad and Ortega Francesc (2009) "Immigration and Housing Booms: Evidence from Spain," IZA Discussion Papers 4333, Institute for the Study of Labor (IZA), Germany.

Katz, Lawrence F. and Kevin M. Murphy (1992) "Changes in Relative Wages 1963-1987- Supply and Demand Factors", *Quarterly Journal of Economics* 107:1, 35-78.

Krusell, P. L. Ohanian, V. Rios-Rull and G. Violante (2000), "Capital-Skill Complementarity and inequality: A Macroeconomic Analysis," Econometrica 68, 1029-53.

Lewis, Ethan (2005) "Immigration, Skill Mix, and the Choice of Technique," Federal Reserve Bank of Philadelphia Working Paper #05-08, May 2005

National Science Foundation (1998) "Survey of Industrial research and development" Division of Science Resource Studies, Washington D.C.

Ottaviano, Gianmarco and Giovanni Peri (2006) "The Economic Value of Cultural Diversity: Evidence from U.S. cities", *Journal of Economic Geography*, Vol. 6, Issue 1, Pages 9-44.

Ottaviano, Gianmarco I.P. and Peri Giovanni (2008) "Immigration and National Wages: Clarifying the Theory and the Empirics" NBER Working Paper 14188, July 2008.

Peri, Giovanni and Chad Sparber (2009) "Task Specialization, Immigration and Wages", *American Economic Journal*: *Applied Economics,* Vol 1:3.

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

Saiz, Albert (2003) "Room in the Kitchen for the Melting Pot: Immigration and Rental Prices." *The Review of Economics and Statistics*, 85 (3), 502-521.

Saiz, Albert (2005) ""Immigration and Housing Rents in American Cities." *Journal of Urban Economics* 61, pp.345-371.

Wooldridge J.L. (2002) *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Boston, MA.

A Appendix: Census Data

A.1 Definition of the Samples

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

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

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

4) Once we calculate experience as age-(time first worked), where (time first worked) is 16 for workers with no HS degree, 19 for HS graduates, 21 for workers with some college education and 23 for college graduates, we eliminate all those with experience <1 and >40.

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

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

Construction of hours worked and employment by cell

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

Construction of the average hourly wage by cell

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

A.2 Individual Variables: Definition and Description

Education: Education groups in each year are defined using the variable EDUCREC which was built in order to consistently reflect the variables HIGRADE and EDUC99. In particular, we define as less educated (L) those with EDUCREC<=7, corresponding to a high school degree or less. Highly educated are those with EDUCREC>=8, corresponding to some college or more.

Experience: Defined as potential experience, assigns to each schooling group a certain age reflecting the beginning of their working life; in particular, the initial working ages are: 17 years for workers with no degree, 19 years for high school graduates, 21 years for those with some college education and 23 years for college graduates.

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

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

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

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

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

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

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

Hourly Wages: The hourly wage for an individual is constructed by dividing the yearly wage as defined above by the number of weeks worked in a year times the number of hours worked in a week.

B Appendix: Construction of Physical Capital by State

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

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

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

Constructing the NAICS97 to SIC87 Concordance

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

We delete everything in the StoN file except the SIC totals (we delete the SIC to NAICS mappings). We then merge these to the NtoS file by SIC code, so that now the NtoS file has the mapping as before, but also includes the totals for each SIC value next to each NAICS-sic pair. Then the percentage can be calculated for each NAICS-sic combination by dividing the NAICS-SIC totals into the merged SIC totals. Since what we actually want is SIC2 to NAICS2, and the original mapping (NtoS) is actually SIC4 to NAICS6, before merging the SIC4 totals into the NtoS file we trimmed the NAICS codes down to 2 digits, and then summed up over the unique SIC4-NAICS2 combinations. We then trimmed the SIC4 values to SIC2, and summed over the unique SIC2-NAICS2 values. Finally, we merged in the SIC2 totals from the StoN file and calculated the percentage of each SIC2 that goes into each NAICS2.

Tables and Figures

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

Explanatory variable is immigration as percentage of initial employment; ***Dependent Variable:***	***(1) basic OLS***	***(2) 1970-2006***	***(3) 1960-2000***	***(4) Including Lagged Dependent variable***	***(5) 2SLS estimates using Immigrant Population Change as instrument***
$\hat{N}$	1.64** (0.50)	1.56** (0.51)	1.61** (0.53)	1.36** (0.57)	1.75** (0.58)
$\hat{y}$	0.66** (0.19)	0.73** (0.18)	0.69** (0.22)	0.74** (0.20)	0.63** (0.19)
Components of $\hat{y}$					
$\left(\frac{\alpha}{1-\alpha}\right)(\hat{K}-\hat{Y})$	-0.53** (0.14)	-0.54** (0.15)	0.47** (0.14)	-0.51** (0.13)	-0.59** (0.14)
$\hat{A}$	1.25** (0.29)	1.32** (0.38)	1.26** (0.31)	1.26** (0.27)	1.26** (0.28)
$\hat{x}$	0.12** (0.02)	0.13** (0.02)	0.12** (0.02)	0.12** (0.03)	0.12** (0.01)
$\hat{\phi}$	-0.16** (0.03)	-0.16** (0.03)	-0.19** (0.03)	-0.15** (0.04)	-0.16** (0.03)
Components of $\hat{\phi}$					
$\hat{h}$	-0.76** (0.13)	-0.80** (0.14)	-0.75** (0.13)	-0.72** (0.12)	-0.76** (0.14)
$\hat{\beta}$	-0.69** (0.08)	-0.73** (0.09)	-0.70** (0.08)	-0.70** (0.09)	-0.67** (0.08)
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 census year 1960-2000 plus 2006. Each regression includes time 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. **=significant at the 5% confidence level. The calculated variables use the assumption that σ=1.75.

Table 2:
2SLS estimates of the impact of immigration on the components of Gross State Product growth
Instruments: imputed immigrants and distance from border/port of entry interacted with decade dummies

Explanatory variable is immigration as percentage of initial employment; ***Dependent Variable:***	***(1)*** ***basic 2SLS***	***(2)*** ***1970-2006***	***(3)*** ***1960-2000***	***(4)*** ***2SLS, including lagged dependent variable***	***(5)*** ***Geography instrument only***
$\hat{N}$	0.90** (0.34)	0.81** (0.34)	0.87** (0.34)	0.70* (0.40)	1.10** (0.50)
$\hat{y}$	0.47** (0.17)	0.48** (0.21)	0.47** (0.21)	0.51** (0.23)	0.37** (0.14)
Components of $\hat{y}$					
$\left(\frac{\alpha}{1-\alpha}\right)(\hat{K}-\hat{Y})$	-0.47** (0.09)	-0.47** (0.10)	-0.44** (0.10)	-0.45** (0.09)	-0.40** (0.10)
$\hat{A}$	1.06** (0.24)	1.13** (0.24)	1.05** (0.26)	1.07** (0.23)	0.90** (0.21)
$\hat{x}$	0.08** (0.02)	0.10** (0.03)	0.07 (0.03)	0.11* (0.03)	0.07* (0.02)
$\hat{\phi}$	-0.21** (0.03)	-0.21** (0.03)	-0.22** (0.03)	-0.24** (0.03)	-0.21** (0.03)
Components of $\hat{\phi}$					
$\hat{h}$	-1.08** (0.08)	-1.13** (0.08)	-1.06** (0.08)	-1.09** (0.09)	-1.11** (0.13)
$\hat{\beta}$	-0.85** (0.12)	-0.93** (0.13)	-0.85** (0.12)	-0.57** (0.13)	-0.84** (0.13)
First stage F-test	36.71	36.52	38.73	44.22	25.03
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 census year 1960-2000 plus 2006. The method of estimation is 2SLS with imputed immigrants and distance from border and from port of entry interacted with decade dummies as instruments. The errors in parenthesis are heteroskedasticity-robust and clustered by state. The calculated variables use the assumption that σ=1.75.

Table 3:
Decomposing the impact of immigration on the capital-output ratio

Explanatory variable is immigration as percentage of initial employment; *Dependent Variable:*	***(1)*** ***basic OLS controlling for initial ln(K/N)***	***(2)*** ***OLS 1970-2006 controlling for initial ln(K/N)***	***(3)*** ***OLS 1960-2000 controlling for initial ln(K/N)***	***(4)*** ***basic 2SLS controlling for initial ln(K/N)***	***(5)*** ***2SLS 1970-2006 controlling for initial ln(K/N)***	***(6)*** ***2SLS 1960-2000 controlling for initial ln(K/N)***
$\hat{K}$	1.38** (028)	1.31** (0.28)	1.92** (0.31)	1.01* (0.37)	0.96** (0.38)	1.46** (0.37)
$\hat{K}-\hat{N}$	-0.09 (0.30)	-0.11 (0.33)	0.35 (0.34)	0.04 (0.36)	0.01 (0.27)	0.32 (0.28)
$\left(\frac{\alpha}{1-\alpha}\right)(\hat{K}-\hat{Y})$	-0.50** (0.17)	-0.53** (0.19)	-0.39 (0.20)	-0.41** (0.13)	-0.42** (0.14)	-0.32* (0.17)
Observations	255	204	204	255	204	204

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 census year 1960-2000 plus 2006. The method of estimation is OLS in column 1 to 3 and 2SLS with imputed immigrants and distance from border interacted with decade dummies as instruments. Each regression includes time dummies as well as the lagged value of (logarithmic) capital per worker in order to control for convergence. The Errors in parenthesis are heteroskedasticity-robust and clustered by state.

Table 4:
Analyzing the impact of immigration on Total Factor Productivity ($\hat{A}$)

Dependent Variable: $\hat{A}$ *Explanatory variables: Immigrants as share of employment*	***(1)*** ***Basic (1960-2006)***	***(2)*** ***Controlling for R&D per worker (1970-2000)***	***(3)*** ***Controlling for Computer Adoption (1970-2000)***	***(4)*** ***Controlling for Trade (period 1980-2006)***	***(5)*** ***Controlling for wage-growth depending on initial sector composition (1960-2006)***
OLS	1.35** (0.30)	1.42** (0.37)	1.17** (0.39)	1.89** (0.32)	1.18** (0.27)
2SLS	1.15** (0.25)	1.11** (0.31)	0.72** (0.26)	1.51** (0.28)	0.94** (0.24)
2SLS *A constructed with σ=1.5*	1.46** (0.38)	1.43** (0.35)	1.21** (0.29)	1.67** (0.33)	1.26** (0.29)
2SLS *A constructed with sigma=2*	1.04** (0.44)	1.00** (0.29)	0.56** (0.25)	1.44** (0.27)	0.84** (0.23)
Explanatory variables:	**Task specialization channel: dependent variable A**				
Change in Employment due to Immigration	0.68* (0.40)	0.55 (0.44)	0.35 (0.38)	1.07** (0.48)	0.43 (0.41)
Change in Communication-Manual specialization of natives	1.20 (1.20)	1.40** (0.70)	2.39** (0.66)	1.62 (1.21)	1.38* (0.72)
Observations	255	153	153	153	255

Note: Each cell in row 1 to 4 is the coefficient of the regression of $\hat{A}$ on the change in employment due to immigrants, estimated including time fixed effects. The baseline estimate (row 1) is OLS with TFP constructed using the assumption that σ=1.75.In the second row we use 2SLS with imputed immigrants and border distance plus distance from New York and Los Angeles, interacted with decade dummies. In the third and fourth row the method of estimation is 2SLS and 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 A 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 census year between 1960 and 2000 plus 2006**.** The errors in parenthesis are heteroskedasticity-robust and clustered by state.

Table 5:

Analyzing the impact of immigration on Skill-Bias ($\hat{\beta}$)

Dependent Variable: $\hat{\beta}$ *Explanatory variables: Immigrants as share of employment*	***(1) Basic***	***(2) Controlling for R&D per worker***	***(3) Controlling for Computer Adoption***	***(4) Controlling for Trade***	***(5) Controlling for initial sector composition***
OLS	-0.72** (0.08)	-0.77** (0.09)	-0.74** (0.09)	-0.86** (0.08)	-0.66** (0.08)
2SLS	-0.93** (0.12)	-0.94** (0.13)	-0.90** (0.13)	-1.04** (0.10)	-0.87** (0.09)
$\hat{\beta}$ *constructed with sigma=1.5*	-1.77* (0.15)	-1.79** (0.20)	-1.91** (0.22)	-1.76** (0.17)	-1.71** (0.17)
$\hat{\beta}$ *constructed with sigma=2*	-0.56** (0.10)	-0.56** (0.09)	-0.48** (0.09)	-0.68** (0.07)	-0.51* (0.07)
Explanatory variables:	**Task specialization channel: dependent variable** $\hat{\beta}$				
Change in Employment due to Immigration	-0.87** (0.15)	-0.71** (0.19)	-0.78** (0.13)	-1.11** (0.19)	-0.88* (0.12)
Change in Communication-Manual specialization of natives	-0.21 (0.47)	-0.36 (0.48)	-0.27* (0.37)	-0.25 (0.39)	-0.20 (0.46)
Observations	255	153	153	153	255

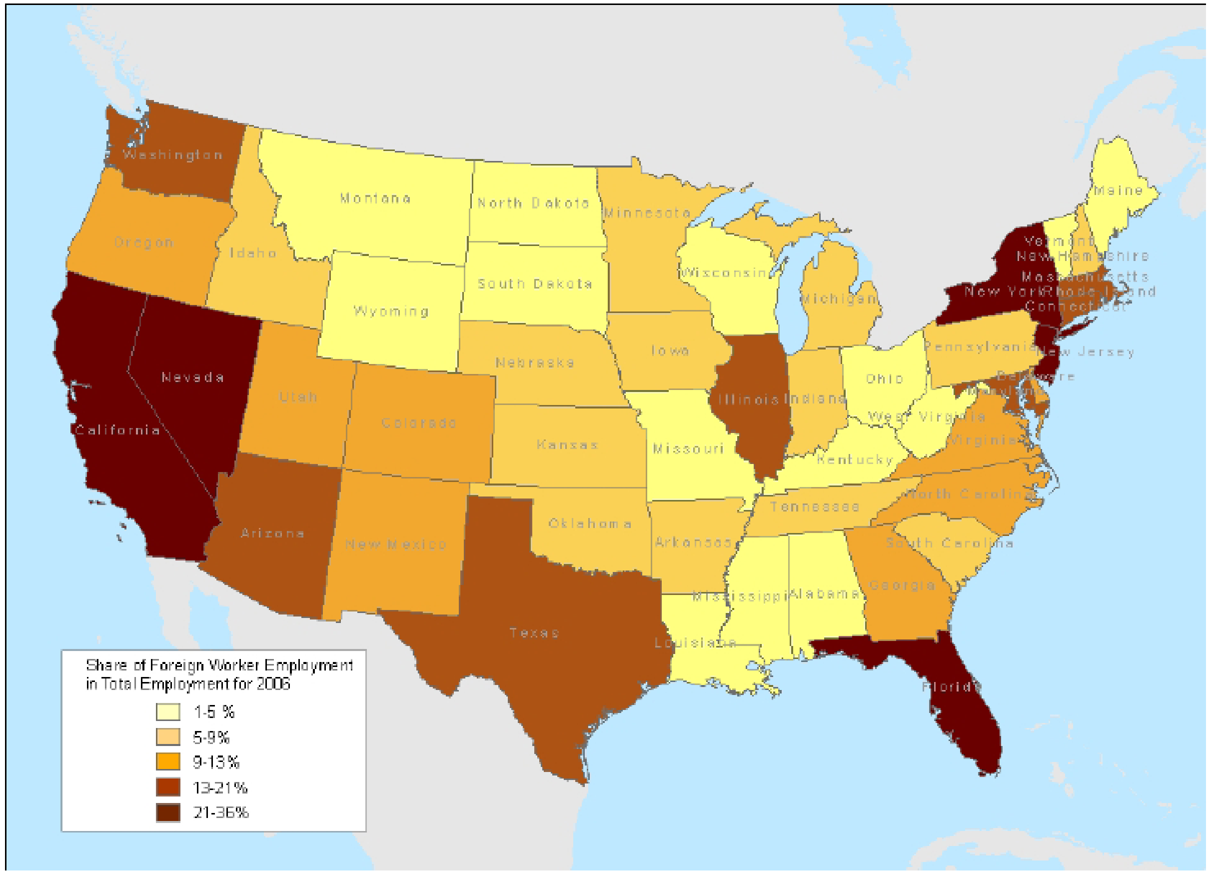
Note: Each cell in row 1 to 4 is the coefficient of the regression of $\hat{\beta}$ on the change in employment due to immigrants, estimated including time fixed effects. The baseline estimate (row 1) is OLS with TFP constructed using the assumption that σ=1.75.In the second row we use 2SLS with imputed immigrants and border distance plus distance from New York and Los Angeles, interacted with decade dummies. In the third and fourth row the method of estimation is 2SLS and 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 A 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 census year between 1960 and 2000 plus 2006**.** The errors in parenthesis are heteroskedasticity-robust and clustered by state.

Table 6:
Robustness check of the main effects

Explanatory variable is immigration as percentage of initial employment; Dependent Variable:	***(1) Basic***	***(2) Controlling for convergence by including initial value***	***(3) No border states (CA,AZ, NM, TX)***	***(4) No largest states (CA, NY, TX)***	***(5) 1980-2006***	***(6) Including region dummies***
$\hat{N}$	0.90**	1.33	0.24	2.36**	0.79**	0.60*
	(0.34)	(0.88)	(1.35)	(0.73)	(0.34)	(0.32)
$\hat{y}$	0.47**	0.76**	2.18**	2.09**	0.70**	0.69**
	(0.17)	(0.21)	(0.47)	(0.51)	(0.26)	(0.30)
$\hat{A}$	1.03**	1.20**	2.58**	2.73**	2.51**	0.96**
	(0.24)	(0.24)	(0.71)	(0.78)	(1.15)	(0.42)
$\hat{\beta}$	-0.85**	-0.43**	-1.36**	-1.07**	-1.07	-1.07**
	(0.11)	(0.09)	(0.30)	(0.26)	(0.10)	(0.10)
Observations	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 census year 1960-2000 plus 2006. The method of estimation is2SLS with imputed immigrants and distance from border interacted with decade dummies as instruments. Each regression includes decade dummies. The Errors in parenthesis are heteroskedasticity-robust and clustered by state. The calculated variables use the assumption that σ=1.75.

Figure 1
Immigrant workers as % of Employment, U.S. States 2006



Note: Data are from the American Community Survey 2006.

]

Figure 2
Real GSP per worker in logarithmic scale
U.S. states, 1960-2006

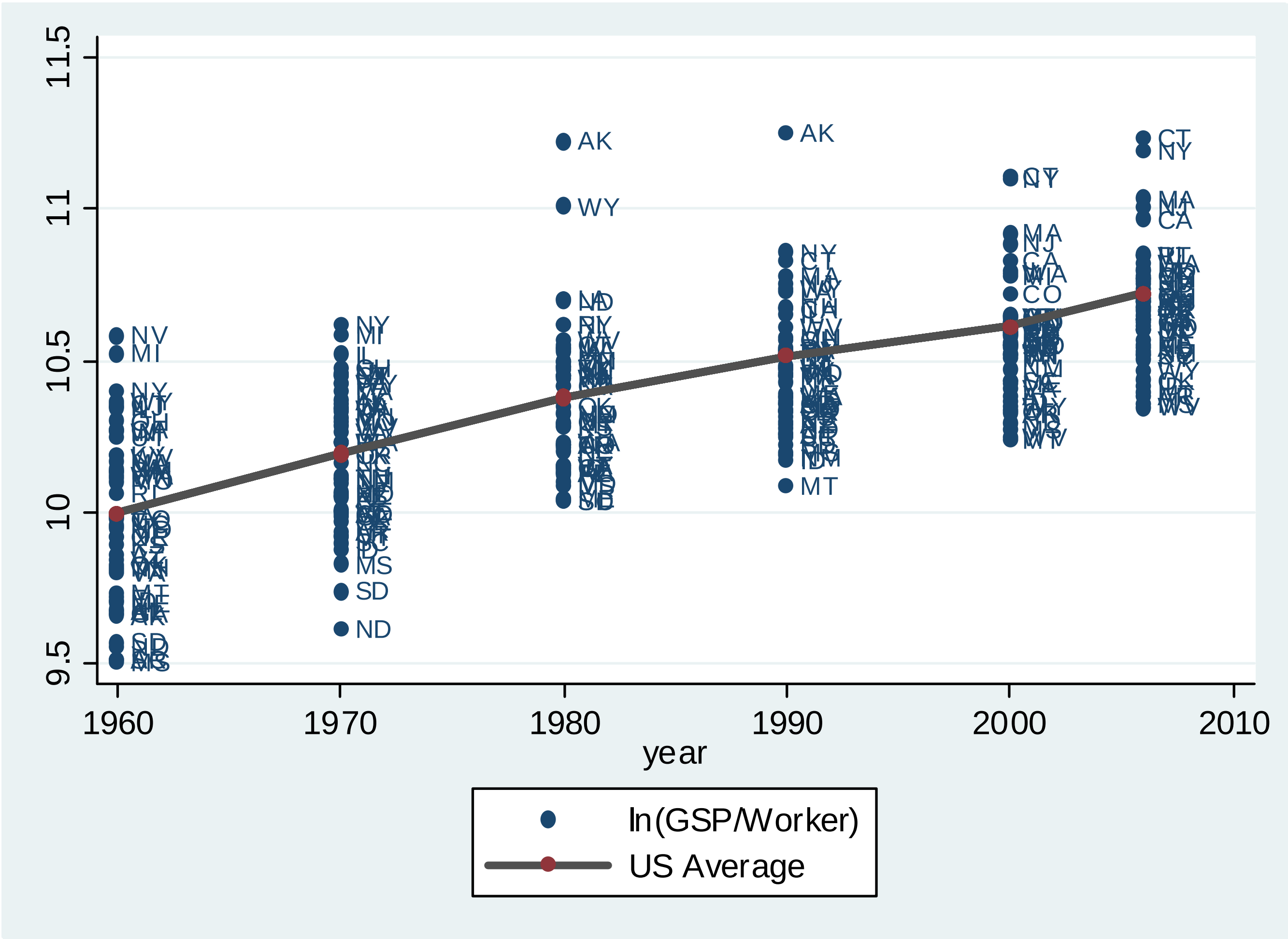


Figure 3
Real capital per worker in logarithmic scale
U.S. states, 1960-2006

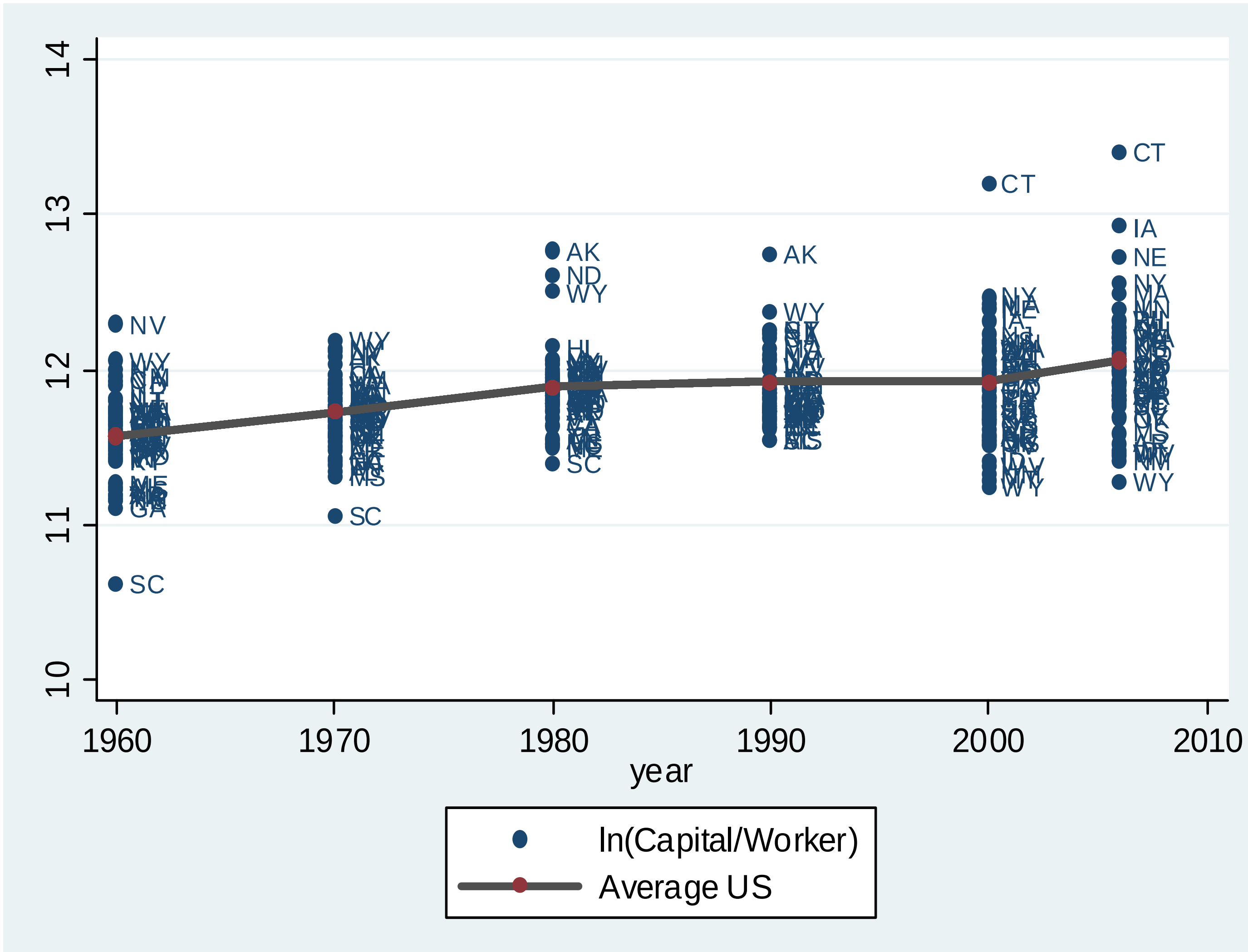


Figure 4
Total Factor Productivity (A) in logarithmic scale
U.S. states, 1960-2006

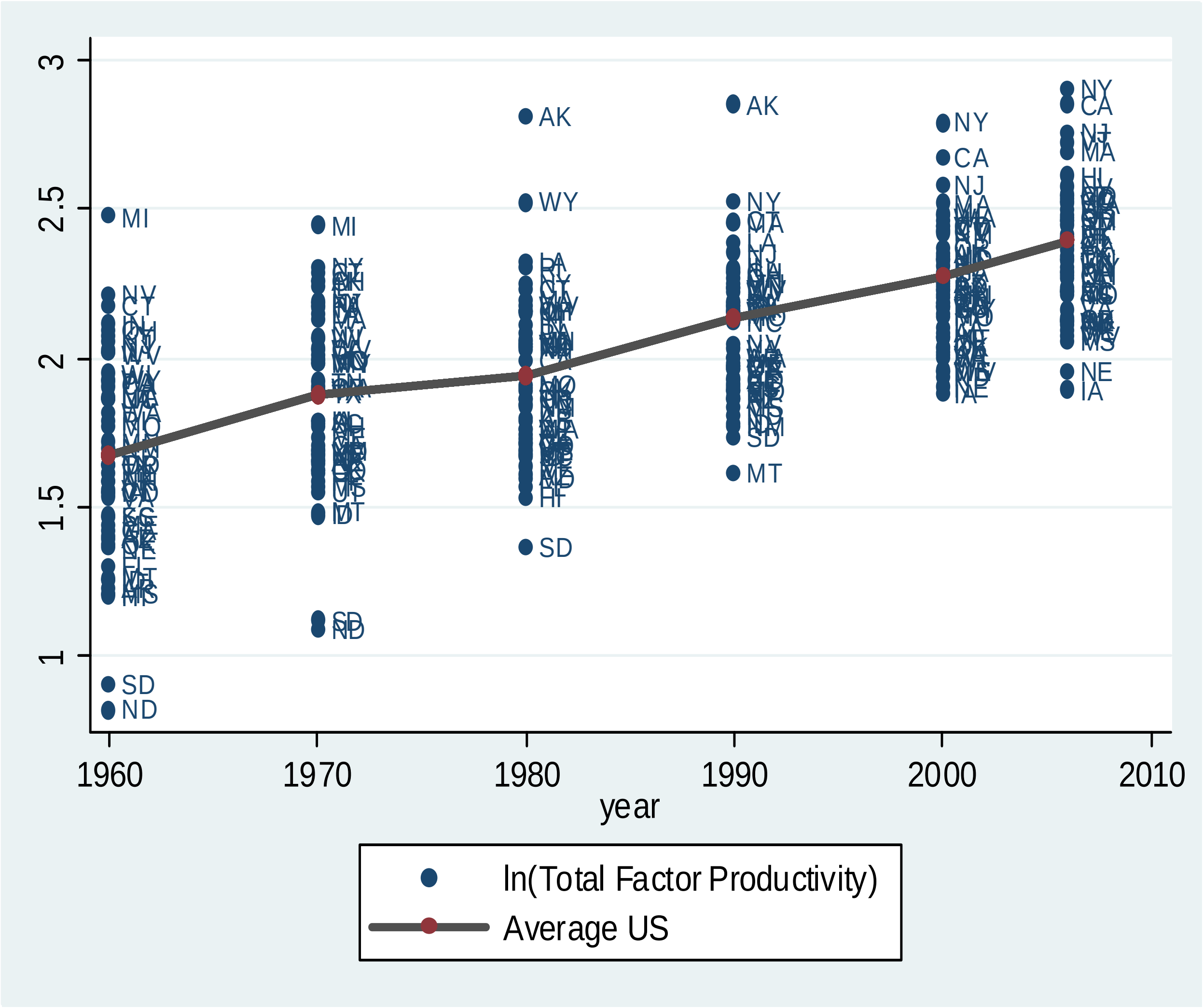


Figure 5
Productivity skill-bias, β
U.S. states, 1960-2006

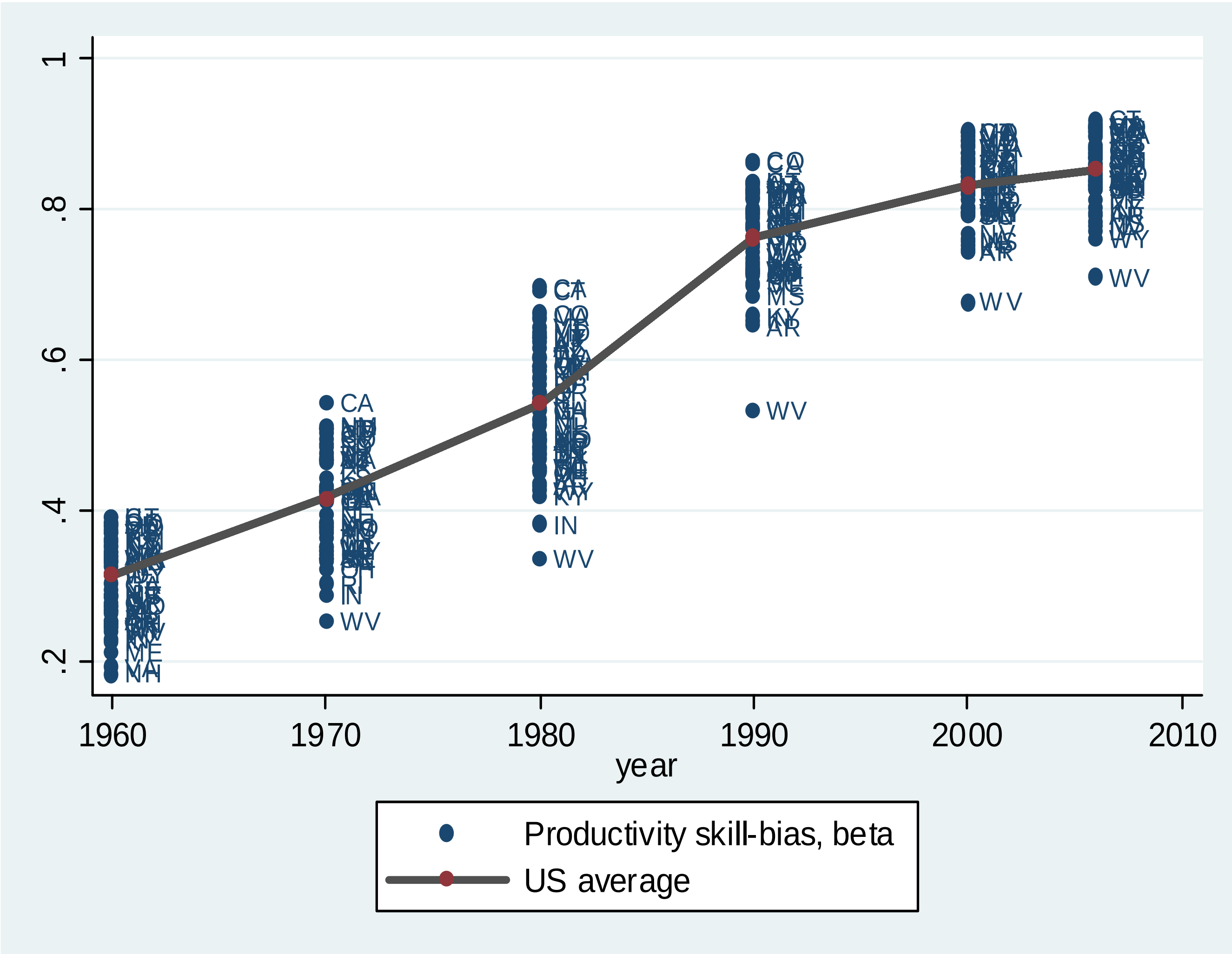


Figure 5
Share of workers with some college education or more, h
U.S. states, 1960-2006

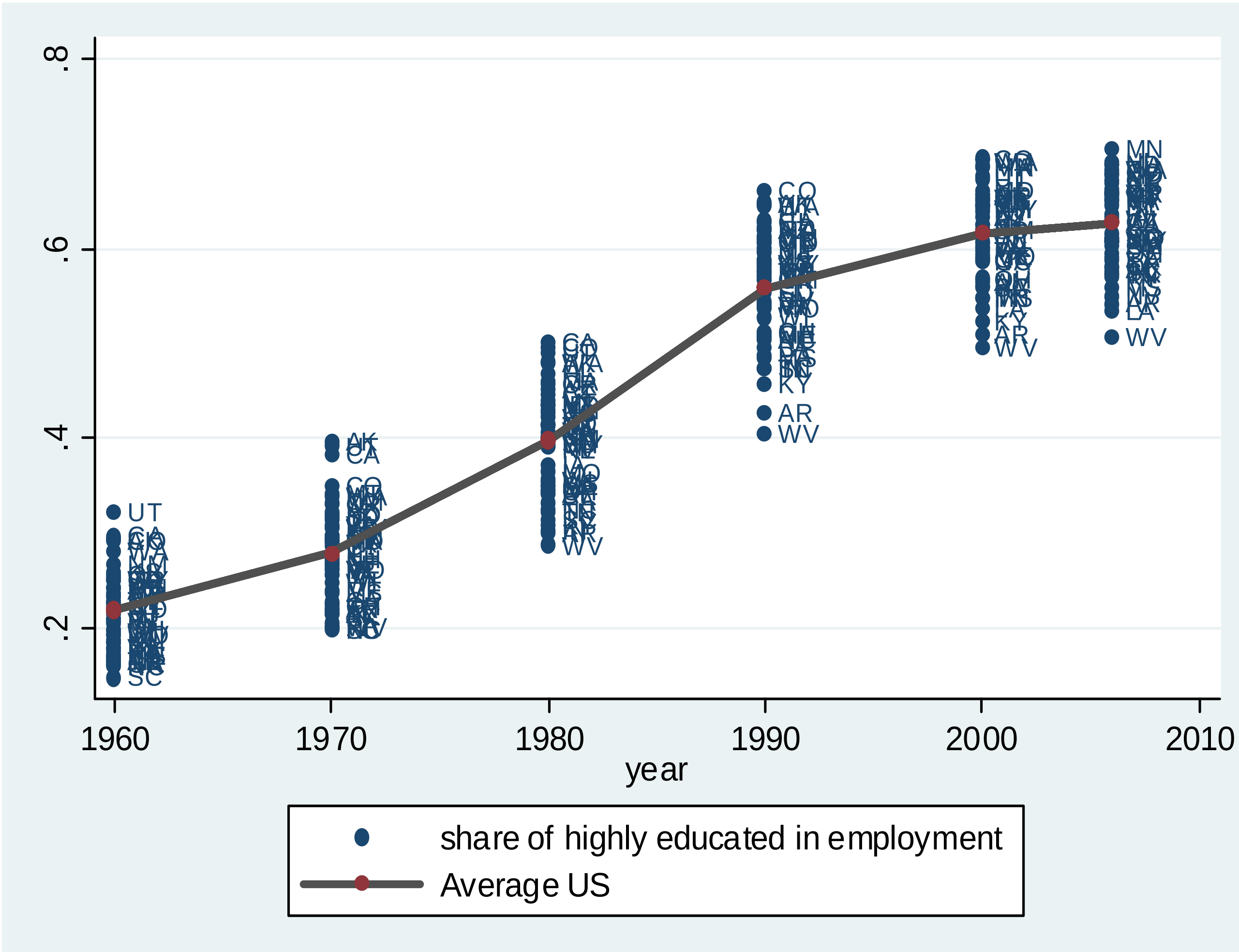


Table Appendix

Table A1: Summary statistics: yearly growth in each decade, average across US states

Annual Growth Rate of:	***60's***	***70's***	***80's***	***90's***	***2000-2006***
Foreign Employment (as percentage of total)	0.1%	0.3%	0.25%	0.5%	0.5%
Total Employment ($\hat{N}$)	2.5%	3.2%	2.1%	2.5%	1%
Gross Product per Worker ($\hat{y}$)	1.9%	1.8%	1.3%	0.9%	1.8%
Capital-Output ratio $(\hat{K} - \hat{Y})$	-0.3%	-0.3%	-1%	-0.9%	+0.4%
Total Factor Productivity $\hat{A}$	2.0%	0.6%	1.6%	1.4%	2.0%
Hours per Worker $\hat{x}$	-0.02%	1.2%	0.4%	0.3%	-0.04%
Share of Highly Educated $\hat{h}$	2.1%	3.0%	2.8%	0.9%	0.02%
Skill-bias of Technology $\hat{\beta}$	2.9%	2.6%	3.4%	0.9%	0.4%

Note: The variables are constructed as described in the text. We are reporting the yearly growth rates (averaging across states and years of the decade) by decade for each variable.