International Trade, Immigration and Human Capital: A Bayesian Efficiency Analysis of the 50 U.S. States

(JEL Category: F10, F22, F43, O40, O47)

(Keywords: U.S. state productivity; immigration; international trade; human capital; stochastic frontier analysis; Bayesian approach)

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Abstract

We study the growth effects of two cross-border activities, flow of goods and flows of labor on U.S. state-level productivity. Using a Bayesian approach we estimate a stochastic frontier model to measure the efficiency externalities of state-level exports and immigration to each of the 50 U.S. states. Our results show that state productivity is affected negatively by state exports and immigration. However, when state exports and immigration interact together it raises state efficiency and are complements at the regional level. Incorporating human capital into the model shows that both interactions of immigrants with accumulated human capital at the state level as well as human capital embodied in immigrants entering each state improves state efficiency.

* We would like to thank participants at the fall 2014 Midwest International Economics Meetings at the University of Kansas for their insightful comments and suggestions. All remaining errors are, of course, our own.
1. Introduction

International trade as a percentage of GDP for the United States has increased from 19.76 percent in 1990 to 30.71 percent in 2011, an increase of approximately 55 percent. Correspondingly, immigrants as a percentage of U.S. population have increased from a low of 4.7 percent in 1970 to 13 percent in 2011. This has led to a growing awareness at the U.S. state level of the importance of international trade on regional growth (Leichenko, 2000) and studies on how immigrant inflows affect U.S. labor markets and productivity at the state level (Card, 2005; Peri, 2012). The limited number of studies at the regional level on the impact of trade and immigration on US productivity is in sharp contrast to the extensive research done at the national level (e.g. Alcàla and Ciccone, 2004; Hung et al, 2004; Keller and Yeaple, 2009; Morley, 2006; Ottaviano and Peri, 2005; Ortega and Peri, 2014).

The focus of this study is to see how international trade flows and immigration affects regional growth. We examine the growth effects of two cross-border activities, immigration and international trade, on U.S state productivity using a Bayesian stochastic frontier model to measure the efficiency externalities of immigration flows to each of the 50 U.S. states and the exports of each U.S state. By examining how state productivity is affected by international economic activities in the goods market (international trade) and the labor market (immigration) this study contributes to the existing literature on the impact of globalization on growth at the regional level in three ways. First, to the best of our knowledge, this is the first study to examine the efficiency impact of immigration and trade on the total factor productivity of the 50 U.S. states. While there are limited studies on the impact of state exports on state growth (Leichenko, 2000) and the impact of immigration on regional total factor productivity (Peri, 2012), there have been no studies that include both these factors simultaneously to examine the nexus between
these two channels and their impact on regional growth. By including both channels we are also able to study how the results of the trade-immigration literature, which are typically conducted at the national level, compare to the results at the regional level.¹

Second, earlier studies on how trade or immigration affects state economic growth have not used the stochastic frontier framework which allows us to look at state output growth from the perspective of a production possibilities frontier. A U.S. state could be operating either on or within the production frontier, and the distance from the frontier reflects inefficiency. Over time, a state’s frontier can shift, which indicates technological change, or a state can move towards or away from the frontier, which represents efficiency changes. A state can also move along the frontier by changing inputs. Productivity growth, therefore, can be seen as being made up of three components: efficiency change, technology change and input change, with the first two components being the “productivity change” (Koop et al 2000). Stochastic frontier analysis thus allows us to distinguish whether productivity changes are due to efficiency gains or losses and technical progress. In addition, it allows us to include explanatory variables in both the production function and the efficiency term.

Third, this study acknowledges the endogenous growth models of Lucas (1988) and Romer (1990) where persistent economic growth is conditional on the accumulation of human capital which helps advance the technological frontier and improves state productivity. We include it as both an existing stock at the state level as well as in the form of additional human capital brought by immigrants into each state. This will reveal how human capital accumulation in each state impacts the efficiency levels of state exports and immigrants into the state since the

¹ The literature on the immigrant-trade linkages typically uses the gravity model to show how immigrants affect bilateral trade between the host country and its trading partners. Meta-analysis of the existing literature on the impact of the immigration on trade at the national level shows that a 10% increase in immigrants increases the host country’s trade volume by about 1%-5% (Lin, 2011 and Genc et al, 2011).
stock of human capital determines how well an economy absorbs the transfer of knowledge and technology that occurs through both international trade and migration. Our model also includes the human capital that immigrants bring with them to the host state which can, in turn, contribute to the host country’s human capital base and thus affect the states’ total factor productivity. Also, by including human capital in the empirical framework we can ensure that efficiency changes due to human capital are not interpreted as changes arising from state exports or immigration.

Our results show that state efficiency is affected negatively by state exports and immigration. However, when state exports and state immigration interact together, they increase state productivity and have a complementary relationship. After human capital is included in the model we find that both interactions of immigrants with accumulated human capital at the state level as well as the human capital embodied in immigrants entering each state improves state efficiency.

The remainder of the paper is organized as follows. In section 2, we discuss the existing literature on the linkages between immigration, trade and productivity. We then construct the empirical model in section 3 and discuss the data in section 4. In section 5, we discuss the empirical results and conclude in section 6.

2. Immigration, Trade, Human Capital and U.S. State-level Productivity

Total factor productivity of a U.S. state could increase through increased flows of goods (as measured by state exports) and increased flows of labor (as measured by immigration into each state). Additionally, we know that human capital also increases total factor productivity.$^2$

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$^2$ Growth economists have done extensive work on the role of human capital in the process of economic growth (e.g. Barro, 2001; Barro and Sala-i-Martin, 1995; Benhabib and Spiegal, 1994; O’Neil, 1995).
In this section we briefly review the literature on the impact of state exports, state immigration inflows and human capital affect total factor productivity at the regional level.

At the national level, countries that trade more have higher rates of technological progress due to their access to a larger international market that provides technological spillover effects and higher profits to innovators, as well as from the economies of scale in research and development (Grossman and Helpman 1990, 1991; Krugman, 1990; Rivera-Batiz and Romer, 1991). Additionally, a more open economy leads to more efficient techniques of production and better access to investment goods which leads to faster productivity growth and, hence, higher real per capita income (Romer 1992; Barro and Sala-i-Martin, 1995). Endogenous growth theory, by emphasizing the importance of knowledge spillovers, lends itself well to analysis on how trade affects growth at the regional level. All regions could gain from growth of exports but regions that choose to specialize in goods with greater potential for spillovers may see higher growth than other regions (Liechenko, 2000). It is with this intent that state governments actively follow export promotion policies with the typical argument being that increased exports by firms in the host-state will lead to regional growth and development. However, there are limited studies that have empirically investigated the impact of state exports on state productivity. Using time-series analysis, Liechenko (2000) examines the causality between foreign exports and U.S. state and regional economic growth using state manufacturing data between 1980 and 1991. They find a bidirectional causal relationship between state exports and

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3 There are several studies which have investigated the impact that state exports to foreign countries have on the economy at the regional level. Coughlin and Cartwright (1987) conduct one of the earliest empirical investigations on whether expenditures on state export promotion policies do have their desired impact on exports. Based on state data from 1980 they find that a $1000 increase in manufacturing export promotion expenditures will generate exports of $432,000. Similarly, Wilkinson’s (1999) study supports the fact that state appropriations for export promotion leads to higher employment for firms that directly export their goods to foreign countries.
state productivity but there are significant regional variations across the country in this relationship.

Immigrants can affect total factor productivity growth by contributing to innovation (Mattoo et al, 2005) or increased knowledge spillovers (Moen, 2005). Additionally, immigrants may have skills that are scarce in the native population which could complement native skills in production or influence the adoption of technology (Lewis, 2005). Peri (2012) is the only study that uses state-level data to investigate the impact of immigrants on productivity. It examines the long-run impact that immigrants have on productivity in 50 U.S. states plus Washington D.C. for each census year from 1960 to 2006. Using a standard neoclassical growth model where the total output of a state increases due to increased employment and capital per worker, the study empirically analyses the impact that immigration has on state employment, capital intensity, total factor productivity, average hours worked and a productivity-weighted skill-intensity index. He finds that immigrants have a significant, positive association with total factor productivity and concludes that, “net inflow of immigrants, even those driven by their historical location and proximity to the border, is associated with significant productivity gains for the receiving states” (p. 357). While Ottaviano and Peri (2006) do not use state-level data, they do a regional analysis at the city-level by examining 160 major metropolitan areas in the US between 1970 and 1990 and conclude that migrant diversity leads to higher productivity of natives in these metro areas.

However, there are several studies that have examined the linkages between immigrants and international trade using US state-level exports (Co et al, 2004; Bandyopadhyay et al., 2008; Bardhan and Guhathakurta, 2005; Dunlevy, 2006; Herander and Saavedra, 2005; White and
These studies show that immigrants increase trade via their preferences for home-country goods as well as network effects that stem from immigrants’ knowledge of the home-country local laws, business practices, and language that reduces transaction costs and increases trade.

Human capital enters the discussion via the impact that state-exports and immigration could have on state-level human capital. Increased trade increases on-the-job human capital accumulation by transferring technology which can increase the knowledge of workers. Grossman and Helpman (1991) suggest that increased trade can interact with human capital resulting in higher economic growth. Immigrants contribute to human capital accumulation in the host country directly via the skills they have acquired before arrival, and indirectly by influencing natives’ knowledge accumulation. Dolado et al. (1994) show that immigrants’ negative impact on output and growth as seen in standard neoclassical growth models is reduced when immigrants arrive with human capital that is higher than the natives. In a recent study, Hanushek et al. (2013) uses US state data to show how state accumulation of human capital influences GDP per capita across states. By combining census micro data on school attainment with cognitive skills constructed from state (or country) of origin achievement test scores, they show that differences in human capital account for 20-30 percent of today’s variation in GDP per capita across states. We thus incorporate human capital in our efficiency model, both as existing stock at the state level as well as via the accumulated stock that immigrants bring with them when they arrive in each state.

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4 This mimics the vast literature at the national level which integrates both trade and immigrant flows to investigate their linkages and to determine whether immigrants increase or decrease trade (Gould, 1994; Head and Reis, 1998; Wagner et al, 2002; White, 2007; Lewer et al, 2008).
3. Data

The data set is a panel of fifty U.S. states for the sample period, 1993-2007. The dependent variable is the log of real GDP (in 2000 dollars) and the independent variables are the log of the labor force (number of workers) and physical capital (in 2000 dollars). The state GDP data is from the U.S. Bureau of Economic Analysis. The labor series is the civilian noninstitutional labor force from the U.S. Bureau of Labor Statistics. The state-by-state capital stock data used in this study was constructed by Garafalo and Yamarik (2002) and updated in Yamarik (2013).

The explanatory variables for the efficiency term are state-level exports, migration and human capital. We use both the human capital stock in each state and the human capital brought by the immigrants into each state. International trade is captured by the variable, Export, which measures the origin of movement of exports by state and is obtained from the Trade Data Services of the US Census Bureau. The data has been converted in to real 2000 dollars. Migration, captured by the variable Migr, was extracted from the Integrated Public Use Microdata Series (IPUMS) database (Ruggles et al, 2010) and captures the number of immigrants that move to each state over the period 1997-2007. The level of education that each immigrant arrives with is also obtained from IPUMS and we classify all immigrants with high school education (number of immigrants with high school degree) or college education (number of immigrants with college degree). We use two measures of human capital accumulated in each state from the U.S. National Bureau of Education Statistics. The first measure is the state population aged 25 years or older with high school education and the second measure is the state population aged 25 years or older with college education. The summary statistics for all the explanatory variables are provided in table A1.
4. Empirical Model

We consider a standard growth model with externalities (Romer, 1986; Lucas, 1988). The product of U.S. state \( i \) at time \( t \), \( Y_{it} \), is determined by the levels of labor input and private capital, \( L_{it} \) and \( K_{it} \). The level of technology or multi-factor productivity is given by the parameter \( A \). The production function is expressed as follows:

\[
Y_{it} = F(A_{it}, L_{it}, K_{it})
\]

The parameter \( A_{it} \) describes the Hicks-neutral productivity and is assumed to be affected by a set of variables, \( Z_{it} \), which are external to a production process of an individual state. We thus rewrite equation (1) as:

\[
Y_{it} = A_{it}(Z_{it})F(L_{it}, K_{it})
\]

Equation (2) shows that the level of total factor productivity, \( TFP_{it} = A_{it}(Z_{it}) \) depends on (embodied and disembodied) technological progress, \( A_{it} \), and on external covariates such as a set of growth determinants, \( Z_{it} \). Among these growth determinants we can consider, for example, the contribution of human capital and open economy measures such as exports and migration.

Following the efficient frontier literature (e.g., Färe et al., 1994), the \( TFP_{it} \) component can be further decomposed into the level of technology, \( A_{it} \), an efficiency measure, \( \tau_{it} \), which depends on the covariates \( Z_{it} \), and a measurement error, \( w_{it} \), which captures the stochastic nature of the frontier,

\[
TFP_{it} = A_{it}\tau_{it}(Z_{it})w_{it}
\]

where \( 0 < \tau_{it} < 1 \). Given the short span of data, we follow Koop (2001) and do not implement a more parameter-rich functional form such as translog, instead we use variants on a Cobb-Douglas production frontier.

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5 When \( \tau_{it} = 1 \) there is full efficiency, in this case the state \( i \) at time \( t \) produces on the efficient frontier.
\[ y_a = \beta_{y0} + \beta_{y1}k_a + \beta_{y2}l_a - u_a + v_a \]  

(4)

where lower case letters indicate the previously defined variables in natural logs [i.e., \( y_{it} = \ln Y_{it} \)], \( u_a = -\ln(\tau_a) \) is a non-negative random variable which measures inefficiency (distance from the efficiency frontier); and \( v_a = \ln(\nu_a) \) is the error term. The model in (4) implies that for each year all states face the same production frontier which, however, may be completely different for each year. The inefficiency "\( u_a " \) and measurement error "\( v_a " \) distributions are always truncated and normal, respectively, but can have different parameters in each year. Following Koop (2001) we assume the frontier parameters evolve in a quadratic fashion over time as:

\[ \beta_j = \beta_{j0} + \beta_{j1}t + \beta_{j2}t^2 \quad j=0, 1, 2 \]

We impose regularity restriction to ensure that capital and labor elasticities are nonnegative at all observed input levels, that is, \( \beta_{11} \geq 0 \) and \( \beta_{22} \geq 0 \). The production frontier technology is assumed to change over time via capital and labor elasticities and technical change, which is assumed to be disembodied and captured by the time-varying intercept.

Expected inefficiency is specified as:

\[ E(u_{it}) = z_{it}\delta_t \]  

(5)

where \( u_{it} \) is assumed to be independently but not identically distributed, \( z_{it} \) is the (1x K) vector of covariates which influence TFP via inefficiency, and \( \delta_t \) is the (K x 1) vector of coefficients to be estimated which vary over time.

We thus model the inefficiency of the 50 states as a function of exports, migration and education:

\[ u_{it} = \delta_{0i} + \delta_{1i}Export_{it} + \delta_{2i}Migr_{it} + \delta_{3i}HSEduc_{it} + \delta_{4i}ColEduc_{it} + \delta_{5i}Migr_{it}*HSEduc_{it} \]

\[ + \delta_{6i}Migr_{it}*ColEduc_{it} + \delta_{7i}Migr_{it}*MigrEdu_{it} + \delta_{8i}Export_{it}*Migr_{it} + \epsilon_{it} \]  

(6)
where, $Exports_{it}$ is the amount of exports from each US state $i$ at time $t$, $Migr$ is migration defined as inflows of foreign population into each state $i$ at time $t$; $HSEduc$ and $ColEduc$ are two measures of human capital defined as the population of state $i$ at the end of year $t$ with high school education and college education, respectively; and $MigrEdu$ is the level of education amongst immigrants and is measured as years of schooling. $Migr_{it}*HSEduc_{it}$, $Migr_{it}*ColEduc_{it}$ and $Migr_{it}*MigrEdu_{it}$ are the interaction terms of immigration and human capital in each state. The hypothesis here is that the effect of immigration on efficiency depends on the level of human capital in each state as well as on the human capital embodied in each immigrant. The interaction between international trade and immigration is captured by $Exports_{it}*Migr_{it}$ and will help shed light on whether they are complements or substitutes. Finally, $\epsilon_{it}$ is white noise. In order to estimate the parameters of the production function in equation (4) together with the parameters in equation (6), we use a Bayesian approach proposed by Koop (2001) which enables us to account for parameter uncertainty which is particularly important for our applied study.

5. Empirical Results

All the models derived from the general specification in (4-6) are fitted by Bayesian methods assuming proper but relatively dispersed prior distributions throughout. For details regarding the empirical model and estimation algorithm refer to the appendix. Table 1 shows the posterior means and numerical standard errors of all parameters of the production frontier. The numerical standard errors prove that our estimates are accurate. Since we assume time-variant parameters and, hence, production elasticities, Figures 1 and 2 plotting the posterior distributions of labour and capital elasticities, are more informative. As displayed, the median values of labor

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6 Fernandez, Osiewalski and Steel (1997) explain that the use of proper priors on the parameters of the composed error term (inefficiency and idiosyncratic random error) is necessary to ensure that the posterior distribution and its moments exist.
and capital output elasticities over time and over US states are around 0.7. Figure 3 displays efficiencies. The histogram looks like a normal, with very low values of output efficiency (mean efficiency around 1.5).

Since we find that inefficiency is significantly present in our sample there is room to investigate its determinants, i.e., the factors that exert an impact on each state’s efficiency and, hence, on its total factor productivity. The analysis is based on equation (6), whose estimates (posterior means) are reported in Table 2. The second column shows the posterior means and the third column the numerical standard error, which indicates that our estimates are quite accurate.\(^7\) Since inefficiency in equation (6) is measured in terms of the distance from the frontier, a negative impact indicates an increase in efficiency (i.e. catching up toward the frontier).

Immigration \((\text{Migr}_t)\) has a positive sign and is statistically significant, indicating that its impact on efficiency is negative in Table 2. In other words, states that have more immigration are less efficient. This is in line with standard neoclassical models where an immigrant as a source of population growth reduces growth. The coefficient on \(\text{Exports}_t\) has a positive sign and is statistically significant, revealing that states that export more are less efficient. This result is in line with the growing body of studies suggesting that exporting confers little or no benefit in the form of faster productivity growth (e.g. Clerides et al. 1998; Bernard and Jensen, 1999; Delgado et al. 2002).

However, when state exports and immigration interact together, \(\text{Export}_t \times \text{Migr}_t\), we see that the sign of the coefficient is negative. This reveals that trade and migration at the regional

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\(^7\) To assesses convergence of the Markov chain Monte Carlo algorithm common practice is to look at the autocorrelation function of the draws. Low autocorrelations suggest that the draws are almost independent, which increases the efficiency of the algorithm. We report in Tables 1 and 2 (last three columns) the numerical standard error (NSE) using Autocovariance Taper calculated using a 4%, 8% and 15% tapered window for the estimation of the spectral density at frequency zero (Geweke, 1992). The low values for all the parameters, except for the intercept, suggest reasonably precise estimates.
level are complements and not substitutes.\textsuperscript{8} The implication of this result is that if a capital abundant North host country opens up to more trade which leads to an increase in exports by the labor-abundant migrant-source South country, then migration will increase after trade liberalization in the host country, source country or both which may be viewed favorably by the host country, especially in the case of skilled migrants (Schiff, 2006).

Human capital accumulation in each state matters only for college-level education in improving efficiency. We also find that immigrants’ interaction with accumulated high school education in each state improves efficiency but not their interaction with accumulated human capital embodied in state college-level education. Additionally, the results in Table 2 show that immigrants increase efficiency if they arrive with human capital. In order to investigate what skill-level matters, we categorize immigrants by their level of education upon arrival. Thus we re-estimate equation (6) but instead of looking at overall human capital embodied by immigrants upon arrival, $Migr_{Edu}$, we specify immigrants with high school education ($Migr_{HSEdu}$) and immigrants with college education ($Migr_{ColEdu}$) in order to determine what skill-level matters for state productivity. In other words, inefficiency is modelled as:

\[
    u_{it} = \alpha_{0t} + \delta_{1t} Export_{it} + \alpha_{2t} Migr_{it} + \alpha_{3t} HSEduc_{it} + \alpha_{4t} ColEduc_{it} + \alpha_{5t} Migr_{it} \times HSEduc_{it} \\
    + \alpha_{6t} Migr_{it} \times ColEduc_{it} + \alpha_{7t} Migr_{it} \times MigrHSEduc_{it} + \alpha_{8t} Migr_{it} \times MigrColEdu_{it} \\
    + \alpha_{9t} Export_{it} \times Migr_{it} + \varepsilon_{it} .
\]

The results are shown in Table 3. All the earlier results from Table 2 hold. Moreover, we now find immigrants that arrive with high school education improve state efficiency but immigrants with college education do not improve efficiency. Thus the human capital

\textsuperscript{8} While the standard Heckscher-Ohlin framework predicts that trade and migration are substitutes, New Trade theory models which incorporate increasing returns to scale and monopolistic competition suggest that trade and migration are complements.
component important for immigrants arriving into each state is high school education. This can be explained by the fact that not all human capital attained by immigrants is transferable to the host country (Basilio and Bauer, 2010) and thus immigrants lack the human capital that is specific to the labor market of the host state. Consequently, high school education amongst immigrants improves state productivity but the college education amongst immigrants does not improve state productivity since it is not specific to the specific state’s labor market. However, we presume that over time they are able to accumulate regional-specific human capital which could enhance state productivity. These results also conform with Peri (2012)’s study which within a growth accounting framework finds that the efficiency gains from immigrants are larger for less-educated workers.

6. Concluding Remarks

The literature has examined quite extensively the impact of trade and immigration on growth at the national level but there are limited, if any, studies on the impact of trade and immigration on productivity at the regional level. In this paper we investigate the impact of two cross-border activities, immigration and international trade, on U.S state productivity using a stochastic frontier model to measure the efficiency externalities of immigration and exports of each U.S state. We find that state productivity is affected negatively by state exports and immigration and that trade and immigration at the regional level are complements. While the level of human capital accumulated in college-level education by each state matters for state productivity improvements we also find that immigrants’ interaction with accumulated high school education in each state improves efficiency. Additionally, the human capital embodied in immigrants arriving in each state also improves state efficiency.
The policy implications of our result confirm earlier studies that show that skilled immigrants matter for total factor productivity. For example, Hunt and Gauthier-Loiselle (2008) use the 2003 National Survey of College Graduates to show that US immigrants patent at twice the rate that natives do which is explained by the much higher propensity of immigrants to hold degrees in science and engineering. Even if immigrants at the state level do not come in with college-level education, they are more likely than natives to study science and engineering and consequently produce innovations which can increase total factor productivity (Hanson, 2013). Thus while exports and immigration per se do not increase state efficiencies, their interaction with each other as well as immigrants’ embodied human capital and interaction with accumulated human capital does raise state efficiencies.
References


Table 1: Estimation Results of Production Function

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Numerical Standard Error (NSE)</th>
<th>NSE using Autocovariance Taper</th>
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<tbody>
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<td></td>
<td></td>
<td></td>
<td>4%</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>15%</td>
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<td>capital</td>
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<tr>
<td>labor</td>
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<tr>
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<td>region9</td>
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<td>0.0387</td>
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</table>

Notes: Number of observations 734. The estimation is carried out according the Gibb steps described in the Appendix. The Markov chain Monte Carlo (MCMC) algorithm is performed running 50,000 iterations and discarding the first 10,000 in a burn-in phase. We computed the MCMC convergence diagnostic in Geweke (1992) for the estimated parameters and the obtained numerical standard errors show very low values that suggest reasonably precise estimates. The second column shows the posterior means. The third columns reports numerical standard errors (NSE) of all parameters of the production frontier. We computed the numerical standard errors employing a 4%, 8% and 15% autocovariance tapered estimate reported in the fourth, fifth and sixth columns. Variables $\text{region}1 \text{ to region}9$ are as follows: 1=New England; 2=Mid-Atlantic; 3=East North Central; 4=West North Central; 5=South Atlantic; 6=East South Central; 7=West South Central; 8=Mountain; 9=Pacific. The Reference region is 5: South Atlantic.
### Table 2: Estimation Results of Efficiency Model (Equation 6)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Numerical Standard Error</th>
<th>NSE using Autocovariance Taper</th>
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<td></td>
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<tr>
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Notes: Number of observations 734. The estimation is carried out according the Gibb steps described in the Appendix. The Markov chain Monte Carlo (MCMC) is performed running 50,000 iterations and discarding the first 10,000 in a burn-in phase. We computed the MCMC convergence diagnostic in Geweke (1992) for the estimated parameters and the obtained numerical standard errors show very low values that suggest reasonably precise estimates. The second column shows the posterior means. The third columns reports numerical standard errors of all parameters of the production frontier. We computed the numerical standard errors employing a 4%, 8% and 15% autocovariance tapered estimate reported in the fourth, fifth and sixth columns.

### Table 3: Estimation Results of Efficiency Model (Equation 7)

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Notes: Number of observations 734. The estimation is carried out according the Gibb steps described in the Appendix. The MCMC is performed running 50,000 iterations and discarding the first 10,000 in a burn-in phase. We computed the MCMC convergence diagnostic in Geweke (1992) for the estimated parameters and the obtained numerical standard errors show very low values that suggest reasonably precise estimates. The second column shows the posterior means. The third columns reports numerical standard errors of all parameters of the production frontier. We computed the numerical standard errors employing a 4%, 8% and 15% autocovariance tapered estimate reported in the fourth, fifth and sixth columns.
Figure 1
Posterior Distribution of Capital Elasticity

Figure 2
Posterior Distribution of Labor Elasticity
Figure 3
Histogram of Posterior Means of Efficiencies
Appendix

Empirical Model

The stochastic frontier model in the log specification for \( j = 1, \ldots, N \) US States and \( t = 1, \ldots, T \) years is

\[
y = X\beta - u + v, \quad (1)
\]

with:

\[
y = \begin{pmatrix} y_1' & \ldots & y_N' \end{pmatrix}'; \quad y = \begin{pmatrix} y_{j,1} & \ldots & y_{j,T} \end{pmatrix}'
\]

\[
u = \begin{pmatrix} v_1' & \ldots & v_N' \end{pmatrix}'; \quad v = \begin{pmatrix} v_{j,1} & \ldots & v_{j,T} \end{pmatrix}'
\]

and

\[
x = \begin{pmatrix} x_1' & \ldots & x_N' \end{pmatrix}'
\]

where

\[
x_{j,t} = (a \ k_{j,t} \ l_{j,t} \ t_{j,t} \ 0.5t^2 \ tk_{j,t} \ tl_{j,t} \ t^2k_{j,t} \ t^2l_{j,t} \ regional\_dummies)'\]

There are two error terms \( u \) and \( v \), where \( v \) is a vector of iid measurement errors, where we assume

\[
v_{j,t} \sim N(0, \sigma_v^2)
\]

For the vector \( u \) representing inefficiency we assume a truncated normal distribution:

\[
u = Z\gamma + \sigma_u \epsilon
\]

In the case where \( u \) is unrestricted \( \epsilon \sim N(0, I) \). A parsimonious way of restricting the elements in \( u \) to be non-negative is to assume that \( \epsilon \) comes from a left-truncated standard normal distribution with truncation point \( \sigma_{\epsilon}^{-1}Z\gamma \). Therefore, \( Z\gamma + \sigma_{\epsilon} \epsilon \geq 0 \).

The prior structure for the parameters to be estimated is
\[ p(\mathbf{u}, \mathbf{\beta}, \mathbf{\gamma}, \sigma_v^2, \sigma_e^2) = p(\mathbf{u}|\mathbf{\gamma}, \sigma_e^2) \cdot p(\mathbf{\beta}) \cdot p(\sigma_v^2) \cdot p(\sigma_e^2) \]

where the production function parameters are normally distributed and have to fulfill the regularity requirements, i.e. the elasticities (evaluated at the median of the data) have to be positive:

\[ I(\mathbf{\beta}) = \begin{cases} 1 & \text{if elasticities are positive} \\ 0 & \text{otherwise} \end{cases} \]

\[ p(\mathbf{\beta}) \sim N\left(\mathbf{\beta}, \mathbf{B}\right) I(\mathbf{\beta}). \]

The prior distribution of \( \mathbf{\gamma} \) is normal, \( \mathbf{\gamma} \sim N\left(\mathbf{\gamma}, \mathbf{G}\right) \). The prior distribution of the error precision is assumed to be Gamma distribution, \( \frac{1}{\sigma_e^2} = \xi_e \sim \mathcal{G}\left(k_e, \lambda_e\right), \quad \frac{1}{\sigma_v^2} = \xi_v \sim \mathcal{G}\left(k_v, \lambda_v\right) \).

For the conditional posterior structure we obtain

\[ p(\mathbf{\beta}|\mathbf{u}, \mathbf{\gamma}, \sigma_v^2, \sigma_e^2, \mathbf{y}) = p(\mathbf{\gamma}|\mathbf{u}, \mathbf{\beta}, \sigma_v^2) \cdot p(\mathbf{\beta}); \]

\[ p(\sigma_v^2|\mathbf{u}, \mathbf{\beta}, \mathbf{\gamma}, \sigma_e^2, \mathbf{y}) = p(\mathbf{\gamma}|\mathbf{u}, \mathbf{\beta}, \sigma_v^2) \cdot p(\sigma_v^2); \]

\[ p(\mathbf{\gamma}|\mathbf{u}, \mathbf{\beta}, \sigma_v^2, \sigma_e^2, \mathbf{y}) = p(\mathbf{\gamma}|\mathbf{u}, \sigma_v^2) \cdot p(\mathbf{\gamma}); \]

\[ p(\sigma_e^2|\mathbf{u}, \mathbf{\beta}, \sigma_v^2, \mathbf{y}, \mathbf{\gamma}) = p(\mathbf{\gamma}|\mathbf{u}, \sigma_e^2) \cdot p(\mathbf{\gamma}); \]

\[ p(\mathbf{u}|\mathbf{\beta}, \mathbf{\gamma}, \sigma_v^2, \sigma_e^2, \mathbf{y}) = p(\mathbf{\gamma}|\mathbf{u}, \mathbf{\beta}, \sigma_v^2) \cdot p(\mathbf{u}|\mathbf{\gamma}, \sigma_e^2). \]

The production function parameter vector are drawn in a Gibbs step (e.g. Casella and George 1992) from a normal distribution rejecting draws which do not fulfill the regularity conditions

\[ \mathbf{\beta}|\mathbf{u}, \mathbf{\gamma}, \sigma_v^2, \sigma_e^2, \mathbf{y} \sim N\left(\mathbf{\beta}, \mathbf{B}\right) I(\mathbf{\beta}) \]

\[ \mathbf{B} = \left(\mathbf{B}^{-1} + \frac{1}{\sigma_v^2} \mathbf{X}'\mathbf{X}\right)^{-1} \]

\[ \tilde{\mathbf{\beta}} = \mathbf{B} \left(\mathbf{B}^{-1}\mathbf{\beta} + \frac{1}{\sigma_v^2} \mathbf{X}'\tilde{\mathbf{y}}\right)^{-1} \]

\[ \tilde{\mathbf{y}} = \mathbf{y} - \mathbf{u} \]
The precision of the measurement error is drawn from a Gamma distribution, and can also be drawn in a Gibbs step:

\[
\frac{1}{\sigma_v^2} = \xi_v | u, y, \beta, \sigma_v^2, \gamma \sim G(k_v, \lambda_v)
\]

\[
\overline{k_v} = k_v + \frac{M}{2} \quad \text{(where M is overall sample size)}
\]

\[
\overline{\lambda_v} = \left( \frac{1}{\overline{\lambda_v}} + \frac{1}{2}(\overline{y} - X\beta)'(\overline{y} - X\beta) \right)^{-1}
\]

The posterior distribution of the parameter vector in the inefficiency term turns out to be

\[
y | u, \beta, \sigma_v^2, \sigma_e^2, y \sim N(\overline{y}, \overline{G})
\]

\[
\overline{G} = \left( G^{-1} + \frac{1}{\sigma_e^2} Z'Z \right)^{-1}
\]

\[
\overline{y} = \overline{G} \left( G^{-1} y + \frac{1}{\sigma_e^2} Z'\overline{u} \right)^{-1}
\]

and for the precision of the measurement error of the inefficiency we obtain

\[
\frac{1}{\sigma_e^2} = \xi_v | u, y, \beta, \sigma_v^2, y \sim G(\overline{k_e}, \overline{\lambda_e})
\]

\[
\overline{k_e} = k_e + \frac{M}{2} \quad \text{(where M is overall sample size)}
\]

\[
\overline{\lambda_e} = \left( \frac{1}{\overline{\lambda_e}} + \frac{1}{2}(\overline{u} - Z\gamma)'(\overline{u} - Z\gamma) \right)^{-1}
\]

Finally the inefficiency posterior is truncated normal distribution \( u_{it} \sim N^+(z_{it} \gamma, \sigma_e^2) \). We draw \( \epsilon_{it} \) from

\[
p(\epsilon_{it} | y, \sigma_e^2) = \frac{1}{\sigma_e \phi(\epsilon_{it})} \frac{\phi(\epsilon_{it})}{\phi \left( \frac{z_{it} \gamma}{\sigma_e} \right)} ; \ i = 1, ..., N; \ t = 1, ..., T.
\]

From \( \epsilon_{it} \) we calculate \( u_{it} = \sigma_e \epsilon_{it} \).
The MCMC is performed running 50,000 iterations and discarding the first 10,000 in a burn-in phase. We computed the MCMC convergence diagnostic in Geweke (1992) for the estimated parameters and the obtained numerical standard errors show very low values that suggest reasonably precise estimates. We computed the numerical standard errors employing a 4%, 8% and 15% autocovariance tapered estimate.
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Notes: The columns report mean and standard deviation of the following variables for each US state. Specifically, the 3rd column shows real GDP (in 2000 dollars); the 4th column shows capital stock (in 2000 dollars); the 5th column shows labor force (number of workers); 6th column shows exports (in 2000 dollars); 7th column gives number of immigrants; 8th column gives the state population aged 25 years or older with high school education; 9th column provides state population aged 25 years or older with college education; 10th column years of education attainment (years of education) of immigrants; 11th column gives the number of immigrants with high school education; and the 12th column gives the number of immigrants with college education.