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

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

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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.

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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]

[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.[3] 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

[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

Tadesse, 2008).[4] These studies show that immigrants increase trade via their preferences for home-country goods as well 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.

[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:

$$Y_{it} = F(A_{it}, L_{it}, K_{it}) \tag{1}$$

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:

$$Y_{it} = A_{it}(Z_{it})F(L_{it}, K_{it}) \tag{2}$$

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, τ_{it}, which depends on the covariates Z_{it}, and a measurement error, w_{it}, which captures the stochastic nature of the frontier,

$$TFP_{it} = A_{it}\tau_{it}(Z_{it})w_{it} \tag{3}$$

where $0 < \tau_{it} < 1$.[5] 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

[5] When $\tau_{it} = 1$ there is full efficiency, in this case the state i at time *t* produces on the efficient frontier.

$$y_{it} = \beta_{t0} + \beta_{t1} k_{it} + \beta_{t2} l_{it} - u_{it} + v_{it} \tag{4}$$

where lower case letters indicate the previously defined variables in natural logs [i.e., $y_{it} = \ln Y_{it}$)], $u_{it} = -\ln(\tau_{it})$ is a non-negative random variable which measure inefficiency (distance from the efficiency frontier); and $v_{it} = \ln(w_{it})$ 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_{it}" and measurement error "v_{it}" 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:

$$\beta_{tj} = \beta_j + \beta_j t + \beta_j t^2 \qquad j=0,\ 1,\ 2$$

We impose regularity restriction to ensure that capital and labor elasticities are nonnegative at all observed input levels, that is, $\beta_{t1} \geq 0$ and $\beta_{t2} \geq 0$. 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:

$$E(u_{it}) = z_{it}\delta_t \tag{5}$$

where u_{it} is assumed to be independently but not identically distributed, $\mathbf{z_{it}}$ is the (1x K) vector of covariates which influence TFP via inefficiency, and δ_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:

$$\begin{aligned} u_{it} = {} & \delta_{0t} + \delta_{1t} Export_{it} + \delta_{2t} Migr_{it} + \delta_{3t} HSEduc_{it} + \delta_{4t} ColEduc_{it} + \delta_{5t} Migr_{it} {*} HSEduc_{it} \\ & + \delta_{6t} Migr_{it} {*} ColEduc_{it} + \delta_{7t} Migr_{it} {*} MigrEdu_{it} + \delta_{8t} Export_{it} {*} Migr_{it} + \varepsilon_{it} \end{aligned} \tag{6}$$

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 $Export_{it}*\ Migr_{it}$ and will help shed light on whether they are complements or substitutes. Finally, ε_{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.[6] 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

[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 ($Migr_{it}$) 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 $Exports_{it}$ 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, $Export_{it}*Migr_{it}$, we see that the sign of the coefficient is negative. This reveals that trade and migration at the regional

[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.[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, *MigrEdu*, we specify immigrants with high school education (*MigrHSEdu*) and immigrants with college education (*MigrColEdu*) in order to determine what skill-level matters for state productivity. In other words, inefficiency is modelled as:

$$\begin{aligned} u_{it} = \alpha_{0t} &+ \delta_{1t}Export_{it} + \alpha_{2t}Migr_{it} + \alpha_{3t}HSEduc_{it} + \alpha_{4t}ColEduc_{it} + \alpha_{5t}Migr_{it}{*}HSEduc_{it} \\ &+ \alpha_{6t}Migr_{it}{*}ColEduc_{it} + \alpha_{7t}Migr_{it}{*}\,MigrHSEdu_{it} + \alpha_{8t}Migr_{it}{*}MigrColEdu_{it} \\ &+ \alpha_{9t}Export_{it}{*}Migr_{it} + \varepsilon_{it}\,. \end{aligned} \tag{7}$$

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

[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

Alcàla, F. and Ciccone, A. 2004. Trade and productivity, *Quarterly Journal of Economics*, 119 (2), 613-646.

Bandyopadhyay, S., Coughlin, C.C., Wall, H.J., 2008. Ethnic networks and state exports. *Review of International Economics* 16 (1), 199–213.

Bardhan, A.D., Guhathakurta, S., 2005. Global linkages of subnational regions: coastal exports and international networks. *Contemporary Economic Policy* 22 (2), 225–236.

Barro, R.J., 2001. Human capital and growth, *American Economic Review* 91, 12-17.

Barro, R. J. & Sala-i-Martin, X. (1995). *Economic growth*. New York: McGraw Hill.

Basilio, T.L and Bauer, T., 2010. The transferability of human capital and immigrant assimilation: An analysis for Germany, Institute for the Study of Labor Discussion Paper No. 4716.

Benhabib, J. and Spiegel, M., 1994. The role of human capital in economic development: evidence from aggregate cross-country data, *Journal of Monetary Economics* 34, 143–173

Bernard, A.B. and Jensen, J.B., 1999. Exceptional Exporter Performance: Cause, Effect, or Both? *Journal of International Economics*, 47:1, 1-26.

Card, D., 2005. "Is the new immigration really so bad?" *Economic Journal* 115, 300–323.

Clerides, S., Lach, S. and Tybout, J. (1998) Is 'Learning-by-Exporting' Important? *Quarterly Journal of Economics*, 113:3, 903-947.

Co, C.Y, Euzent, P., Thomas, M., 2004. The export effect of immigration into the USA, *Applied Economics* 36, 573-583.

Coughlin, C.C. and Cartwright, P.A., 1987. An examination of state foreign export promotion and manufacturing exports, *Journal of Regional Science* 27(3), 439-449.

Delgado, M., Fariñas, J. and Ruano, S., 2002. Firm Productivity and Export Markets: A Nonparametric Approach. *Journal of International Economics*, 57:2, 397-422.

Dolado, J.J., Goria, A., and Ichino, A., 1994. Immigration, human capital and growth in the host country: evidence from pooled country data, *Journal of Population Economics*, 7 (2), 193-215.

Dunlevy, J.A., 2006. The influences of corruption and language on the protrade effect of immigrants: evidence from the American States. *Review of Economics and Statistics* 88 (1), 182–186

Färe, R., Grosskopf, S., and Lovell, C.A. Knox, 1994. Production frontiers. Cambridge University Press, Cambridge, New York, and Melbourne. pp. xv, 296.

Fernandez, C., Osiewalski, J. and Steel, M., 1997. On the use of panel data in stochastic frontier models with improper priors, *Journal of Econometrics*, 79,169–193.

Garafalo, G., Yamarik, S., 2002. "Regional Convergence: Evidence From A New State-By-State Capital Stock Series," *The Review of Economics and Statistics*, 84(2), 316-323.

Genc, M., Gheasi, M., Nijkam, P., Pot, J., 2011. The impact of immigration on international trade: A meta-analysis. IZA Discussion Papers, Number 6145.

Geweke, J. (1992), "Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments", in J. M. Bernardo, J. Berger, A. P. Dawid and A. F. M. Smith (eds.) Bayesian Statistics (Oxford: Oxford University Press) 169–193.

Grossman, G. M., Helpman, E., 1990. Comparative advantage and long run growth, *American Economic Review* 80, 796-815.

Grossman, G.M., Helpman, E., 1991. Innovation and growth in the global economy. MIT Press, Cambridge, MA.

Gould, D.M., 1994. Immigrant links to the home country: empirical implications for United States bilateral trade flows. *Review of Economics and Statistics* 76 (2), 302–316

Hanson, G., 2013. "Immigration, Productivity, and Competitiveness in American Industry," in Kevin Hassett, ed., *Rethinking Competitiveness*, Washington, DC: AEA Press, 95-131.

Hanushek, E.A., Ruhose, J, Woesmann, L., 2014. The importance of state human capital, unpublished paper presented at the American Economic Association Meetings, Philadelphia, PA.

Head, K., Ries, J., 1998. Immigration and trade creation: econometric evidence from Canada. *Canadian Journal of Economics* 31(1), 47-62.

Herander, M.G., Saavedra, L.A., 2005. Exports and the structure of immigrant-based networks: the role of geographic proximity. *Review of Economics and Statistics* 87 (2), 323–335.

Hung, J, Salomon M, Sowerby, S., 2004. International trade and US productivity, *Research in International Business and Finance*, 18(1), 1-25.

Hunt, J., Gauthier-Loiselle, M. 2008. "How much does immigration boost innovation?" NBER Working Paper No. 14313.

Keller, W., Yeaple, S.R., 2009. Multinational enterprises, international trade, and productivity growth: Firm-level evidence from the United States, *The Review of Economics and Statistics,* 91 (4), 821-831.

Koop, G., 2001. Cross-sectoral patterns of efficiency and technical change in manufacturing, *International Economic Review*, 42, 73-103.

Koop, G., Osiewalski, J. and Steel, M., 2000. Modelling the sources of output growth in a panel of countries, *Journal of Business and Economic Statistics*, 3, 284–99.

Krugman, P. R. (1990). *Rethinking international trade*. Cambridge, MA: MIT Press.

Lewer, J.J., Van den Berg, H., 2008. A gravity model of immigration, *Economics Letters* 99(1), 164-167

Lewis, E., (2005) "Immigration, skill mix and the choice of technique", Federal Reserve Bank of Philadelphia, Working Paper No. 05-8.

Leichenko, R.M, 2000. Exports, employment and productions: A causal assessment of U.S. States and Regions, *Economic Geography*, 76(4), 303-325.

Lin, F., 2011. The pro-trade impacts of immigrants: a meta-analysis of network effects. *Journal of Chinese Economic and Foreign Trade Studies* 4 (1), 17–27.

Lucas Jr., R.E., 1988. On the mechanics of economic development, *Journal of Monetary Economics* 22, 3-42.

Mattoo, A., K. E. Maskus, and G. Chellaraj, 2005. "The contribution of skilled immigration and international graduate students to U.S. innovation." The World Bank, Policy Research Working Paper Number 3588.

Moen, J., 2005. "Is mobility of technical personnel a source of R&D spillovers?" *Journal of Labor Economics*, 23(1), 81-114.

Morley, B., 2006. Causality between economic growth and immigration: An ARDL bounds testing approach, *Economics Letters* 90, 72-76

O'Neill, D., 1995. Education and income growth: implications for cross-country inequality, *Journal of Political Economy*, 103 (6), 1289-1301.

Ortega, F., Peri, G. 2014. Openness and income: The roles of trade and migration. *Journal of International Economics* 92(2), 231-251.

Ottaviano, G, Peri, G., 2005. Rethinking the gains from immigration: theory and evidence from the US, NBER working paper No. 11672.

Ottaviano G, Peri, G., 2006. The economic value of cultural diversity: evidence from US cities, *Journal of Economic Geography* 6, 9 – 44.

Peri, G., 2012. The Effect of immigration on productivity: evidence from U.S. States, *Review of Economics and Statistics* 94(1), 348-358.

Rivera-Batiz. L. A. & Romer P. M. ,1991. International trade with endogenous technological change, *European Economic Review* 35**,** 971 – 1004

Romer, P.M., 1990. Endogenous technological change, *Journal of Political Economy*, 98 (5), S71-102.

Romer, P.M., 1992. Growth based on increasing returns due to specialization, *The New Classical Macroeconomics* 3, 569-575.

Romer, P.M., 1986. Increasing returns and long-run growth, *Journal of Political Economy*, 94 (5), 1002-1037.

Ruggles, S, Alexander, T., Genadek, K, Goeken, R. Schroeder, M.B., Sobek. M. (2010) *Integrated Public Use Microdata Series: Version 5.0* [Machine-readable database]. Minneapolis: University of Minnesota.

Schiff, M. 2006. Migration, Investment and Trade: Substitutes or Complements? Working Paper. Weltbank, Universidad de Chile and IZA.

Wagner, D., Head, K., Ries, J., 2002. Immigration and the trade of provinces, *Scottish Journal of Political Economy* 49(5), 507-525.

White R., 2007. Immigrant-trade links, transplanted home bias and network effects, *Applied Economics* 39(7), 839–52.

White R, and Tadesse, B., 2008. Immigrants, cultural distance and U.S. state-level exports of cultural products, *North American Journal of Economics and Finance* 19, 331-348.

Yamarik, S, 2013. "State-level capital and investment: Updates and implications," C*ontemporary Economic Policy* 31(1), 62-72.

Wilkinson, 1999. The effect of state appropriations on export-related employment in manufacturing. *Economic Development Quarterly* 13, pp 172-182.

Table 1: Estimation Results of Production Function

Parameter	Estimate	Numerical Standard Error (NSE)	NSE using Autocovariance Taper 4%	8%	15%
constant	-3.9079	0.2077	0.7504	0.7358	0.6157
capital	0.7514	0.0207	0.0845	0.0833	0.0725
labor	-0.0614	0.0269	0.1117	0.1079	0.0940
time	-2.6466	0.0622	0.3054	0.2714	0.2143
capital*time	-0.0014	0.0053	0.0206	0.0196	0.0139
labor*time	0.1891	0.0065	0.0254	0.0240	0.0169
Time ^{2}	0.1691	0.0051	0.0242	0.0206	0.0157
capital*(time ^{2})	-0.0002	0.0004	0.0018	0.0016	0.0011
labor*(time ^{2})	-0.0116	0.0005	0.0018	0.0017	0.0012
region1	0.0200	0.0121	0.0431	0.0433	0.0361
region2	-0.4274	0.0151	0.0601	0.0553	0.0495
region3	-0.3318	0.0125	0.0342	0.0282	0.0278
region4	-0.0559	0.0119	0.0502	0.0468	0.0391
region6	-0.2313	0.0133	0.0496	0.0522	0.0523
region7	-0.3616	0.0135	0.0528	0.0517	0.0473
region8	0.0165	0.0117	0.0503	0.0458	0.0378
region9	-0.1033	0.0125	0.0387	0.0312	0.0282

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 *region1* to *region9* 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)

Parameter	Estimate	Numerical Standard Error	NSE using Autocovariance Taper 4%	8%	15%
constant	3.2620	0.3136	0.2915	0.2957	0.2531
Migr	0.8672	0.0591	0.0800	0.0836	0.0934
HSedu	1.2601	0.1508	0.1441	0.1523	0.1554
Coledu	-1.3270	0.1456	0.1368	0.1384	0.1304
Migr.*Hsedu	-0.1323	0.0160	0.0146	0.0154	0.0159
Migr.*Coledu	0.1396	0.0154	0.0139	0.0140	0.0134
Migr*EduMigr	-0.0137	0.0168	0.0232	0.0236	0.0259
Migr.*Export	-0.0344	0.0029	0.0039	0.0044	0.0048
Export	0.3136	0.0251	0.0330	0.0375	0.0407

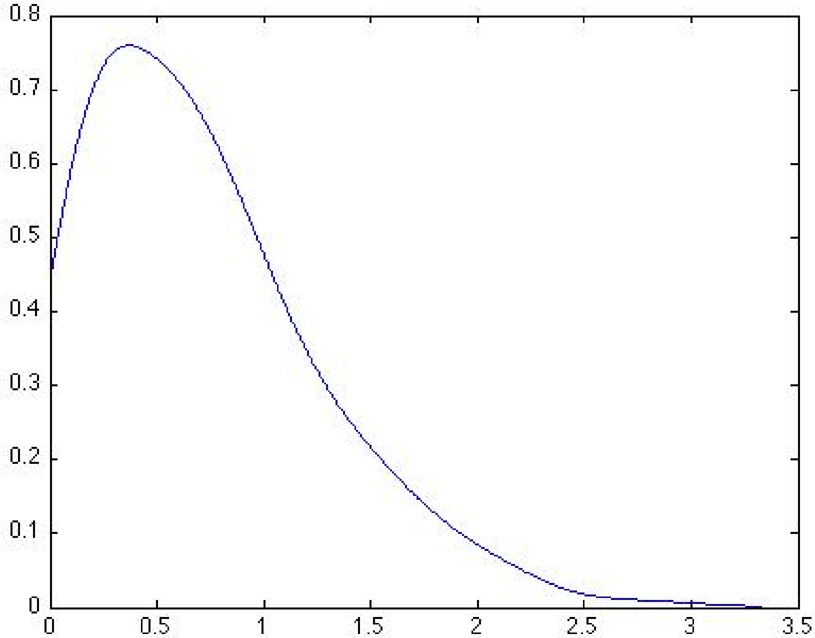
Notes: Number of observations 734. The estimation is carried out according the Gibb steps described in the Appendix. The Markov chain Monte Carlo (MCMC) is performed running 50,000 iterations and discarding the first 10,000 in a burn-in phase. We computed the MCMC convergence diagnostic in Geweke (1992) 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)

Parameter	Estimate	Numerical Standard Error	NSE using Autocovariance Taper 4%	8%	15%
constant	2.4881	0.3207	0.2992	0.2990	0.2687
Migr	0.8610	0.0416	0.0618	0.0714	0.0735
HSedu	1.4502	0.1575	0.1877	0.1844	0.1785
Coledu	-1.5033	0.1523	0.1739	0.1711	0.1656
Migr.*Hsedu	-0.1482	0.0167	0.0197	0.0193	0.0185
Migr*Coledu	0.1532	0.0161	0.0181	0.0179	0.0172
Migr*MigrHSEdu	-0.0044	0.0040	0.0042	0.0040	0.0036
Migr*MigrColEdu	0.0189	0.0038	0.0039	0.0040	0.0036
Migr*Export	-0.0385	0.0030	0.0038	0.0041	0.0043
Export	0.3501	0.0265	0.0333	0.0347	0.0332

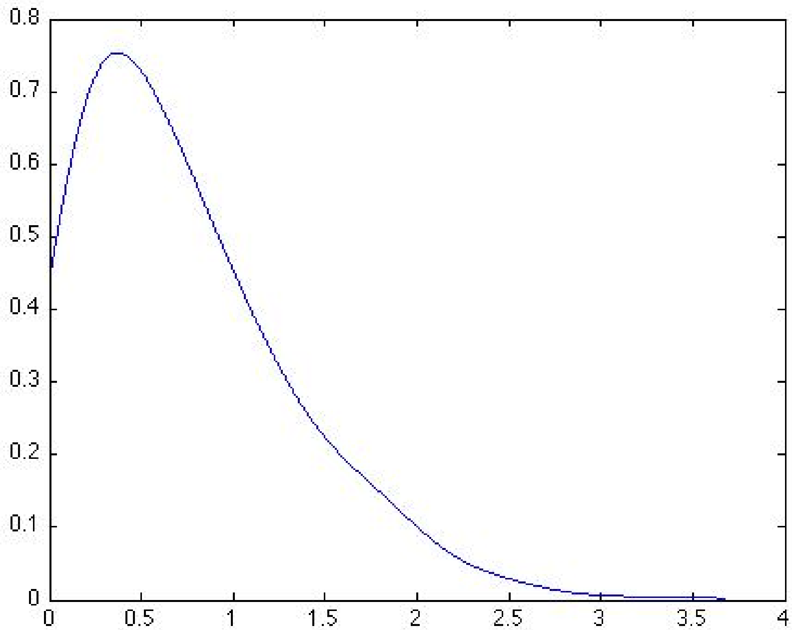
Notes: Number of observations 734. The estimation is carried out according the Gibb steps described in the Appendix. The MCMC is performed running 50,000 iterations and discarding the first 10,000 in a burn-in phase. We computed the MCMC convergence diagnostic in Geweke (1992) for the estimated parameters 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



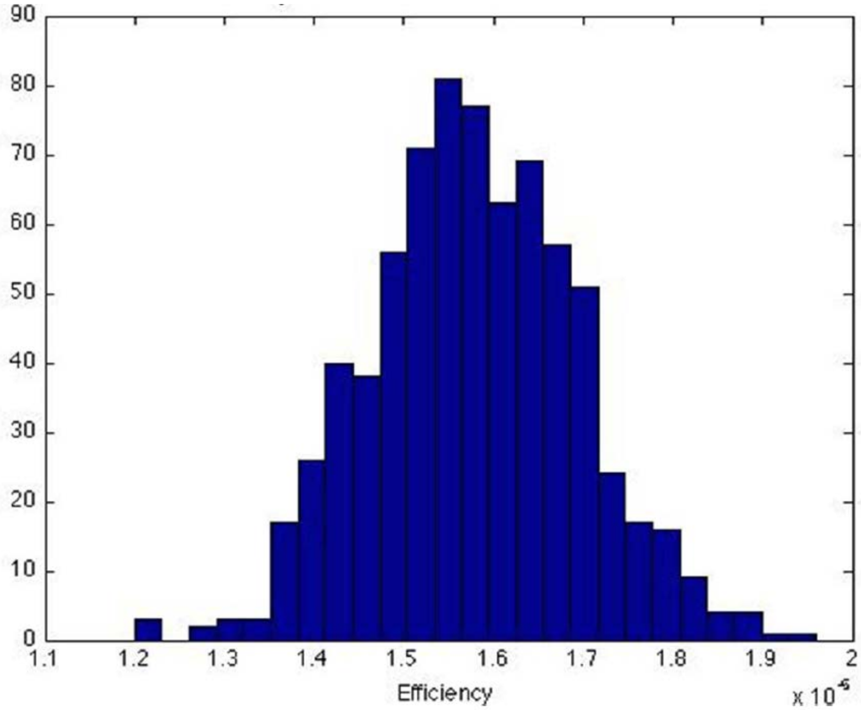
Elasticity values

Figure 2
Posterior Distribution of Labor Elasticity



Elasticity values

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

$\mathbf{y} = \mathbf{X\beta} - \mathbf{u} + \mathbf{v}$, (1)

with:

$$\boldsymbol{y} = (\boldsymbol{y}_1' \ldots \boldsymbol{y}_N')'; \quad \boldsymbol{y} = \left(\boldsymbol{y}_{j,1}' \ldots \boldsymbol{y}_{j,T}'\right)'$$
$$\boldsymbol{u} = (\boldsymbol{u}_1' \ldots \boldsymbol{u}_N')'; \quad \boldsymbol{u} = \left(\boldsymbol{u}_{j,1}' \ldots \boldsymbol{u}_{j,T}'\right)'$$
$$\boldsymbol{v} = (\boldsymbol{v}_1' \ldots \boldsymbol{v}_N')'; \quad \boldsymbol{v} = \left(\boldsymbol{v}_{j,1}' \ldots \boldsymbol{v}_{j,T}'\right)'$$

and

$$\boldsymbol{X} = (\boldsymbol{x}_1' \ldots \boldsymbol{x}_N')'$$

where

$$\boldsymbol{x_{j,t}} = \left(a \;\; k_{j,t} \;\; l_{j,t} \;\; t_{j,t} \;\; 0.5t^2 \;\; tk_{j,t} \;\; tl_{j,t} \;\; t^2k_{j,t} \;\; t^2l_{j,t} \;\; regional\_dummies\right)'$$

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:

$$\boldsymbol{u} = \boldsymbol{Z\gamma} + \sigma_\epsilon \boldsymbol{\epsilon}$$

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

The prior structure for the parameters to be estimated is

$$p(\boldsymbol{u},\boldsymbol{\beta},\boldsymbol{\gamma},\sigma_v^2,\sigma_\epsilon^2) = p(\boldsymbol{u}|\boldsymbol{\gamma},\sigma_\epsilon^2)\, p(\boldsymbol{\beta})\, p(\boldsymbol{\gamma}) p(\sigma_v^2)\, p(\sigma_\epsilon^2)$$

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

$$I(\boldsymbol{\beta}) = \begin{Bmatrix} 1 \text{ } if \text{ } elasticities \text{ } are \text{ } positive \\ 0 \text{ } otherwise \end{Bmatrix}$$

$$p(\boldsymbol{\beta}) \sim N\left(\underline{\boldsymbol{\beta}}, \underline{\boldsymbol{B}}\right) I(\boldsymbol{\beta}).$$

The prior distribution of $\boldsymbol{\gamma}$ is normal, $\boldsymbol{\gamma} \sim N\left(\underline{\boldsymbol{\gamma}}, \underline{\boldsymbol{G}}\right)$. The prior distribution of the error precision is assumed to be Gamma distribution, $\frac{1}{\sigma_v^2} = \xi_v \sim G\left(\underline{k_v}, \underline{\lambda_v}\right)$, $\frac{1}{\sigma_\epsilon^2} = \xi_\epsilon \sim G\left(\underline{k_\epsilon}, \underline{\lambda_\epsilon}\right)$.

For the conditional posterior structure we obtain

$p(\boldsymbol{\beta}|\boldsymbol{u},\boldsymbol{\gamma},\sigma_v^2,\sigma_\epsilon^2,\boldsymbol{y}) = p(\boldsymbol{y}|\boldsymbol{u},\boldsymbol{\beta},\sigma_v^2)\, p(\boldsymbol{\beta})$;

$p(\sigma_v^2|\boldsymbol{u},\boldsymbol{\beta},\boldsymbol{\gamma},\sigma_\epsilon^2,\boldsymbol{y}) = p(\boldsymbol{y}|\boldsymbol{u},\boldsymbol{\beta},\sigma_v^2)\, p(\sigma_v^2)$;

$p(\boldsymbol{\gamma}|\boldsymbol{u},\boldsymbol{\beta},\sigma_v^2,\sigma_\epsilon^2,\boldsymbol{y}) = p(\boldsymbol{u}|\boldsymbol{\gamma},\sigma_\epsilon^2)\, p(\boldsymbol{\gamma})$;

$p(\sigma_\epsilon^2|\boldsymbol{u},\boldsymbol{\beta},\sigma_v^2,\boldsymbol{\gamma},\boldsymbol{y}) = p(\boldsymbol{u}|\boldsymbol{\gamma},\sigma_\epsilon^2)\, p(\boldsymbol{\gamma})$;

$p(\boldsymbol{u}|\boldsymbol{\beta},\boldsymbol{\gamma},\sigma_v^2,\sigma_\epsilon^2,\boldsymbol{y}) = p(\boldsymbol{y}|\boldsymbol{u},\boldsymbol{\beta},\sigma_v^2)\, p(\boldsymbol{u}|\boldsymbol{\gamma},\sigma_\epsilon^2)$.

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 fulfil the regularity conditions

$$\beta|_{\boldsymbol{u},\boldsymbol{\gamma},\sigma_v^2,\sigma_\epsilon^2,\boldsymbol{y}} \sim N(\overline{\boldsymbol{\beta}}, \overline{B})\, I(\boldsymbol{\beta})$$

$$\overline{B} = \left(\underline{B}^{-1} + \frac{1}{\sigma_v^2} X'X\right)^{-1}$$

$$\overline{\beta} = \overline{B}\left(\underline{B}^{-1}\underline{\beta} + \frac{1}{\sigma_v^2}\boldsymbol{X}'\widetilde{\boldsymbol{y}}\right)^{-1}$$

$$\widetilde{\boldsymbol{y}} = \boldsymbol{y} - \boldsymbol{u}$$

The precision of the measurement error is drawn from a Gamma distribution, and can also be drawn in a Gibbs step:

$$\frac{1}{\sigma_v^2} = \xi_v|_{\boldsymbol{u},\boldsymbol{\gamma},\boldsymbol{\beta},\sigma_\epsilon^2,\boldsymbol{y}} \sim G\left(\overline{k_v}, \overline{\lambda_v}\right)$$

$\overline{k_v} = \underline{k_v} + \frac{\boldsymbol{M}}{\boldsymbol{2}}$ (where M is overall sample size)

$$\overline{\lambda_v} = \left(\frac{1}{\underline{\lambda_v}} + \frac{1}{2}(\widetilde{\boldsymbol{y}} - \mathbf{X}\boldsymbol{\beta})'(\widetilde{\boldsymbol{y}} - \mathbf{X}\boldsymbol{\beta})\right)^{-1}$$

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

$$\boldsymbol{\gamma}|_{\boldsymbol{u},\boldsymbol{\beta},\sigma_v^2,\sigma_\epsilon^2,\boldsymbol{y}} \sim N(\overline{\boldsymbol{\gamma}}, \overline{G})$$

$$\overline{\boldsymbol{G}} = \left(\underline{\boldsymbol{G}}^{-1} + \frac{1}{\sigma_\epsilon^2}\boldsymbol{Z}'\boldsymbol{Z}\right)^{-1}$$

$$\overline{\boldsymbol{\gamma}} = \overline{\boldsymbol{G}}\left(\underline{\boldsymbol{G}}^{-1}\underline{\boldsymbol{\gamma}} + \frac{1}{\sigma_\epsilon^2}\boldsymbol{Z}'\widehat{\boldsymbol{u}}\right)^{-1}$$

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

$$\frac{1}{\sigma_\epsilon^2} = \xi_v|_{\boldsymbol{u},\boldsymbol{\gamma},\boldsymbol{\beta},\sigma_v^2,\boldsymbol{y}} \sim G\left(\overline{k_\epsilon}, \overline{\lambda_\epsilon}\right)$$

$\overline{k_\epsilon} = \underline{k_\epsilon} + \frac{\boldsymbol{M}}{\boldsymbol{2}}$ (where M is overall sample size)

$$\overline{\lambda_\epsilon} = \left(\frac{1}{\underline{\lambda_\epsilon}} + \frac{1}{2}(\widehat{\boldsymbol{u}} - \mathbf{Z}\boldsymbol{\gamma})'(\widehat{\boldsymbol{u}} - \mathbf{Z}\boldsymbol{\gamma})\right)^{-1}$$

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

$$p(\epsilon_{it}|\boldsymbol{\gamma}, \sigma_\epsilon^2) = \frac{\frac{1}{\sigma_\epsilon}\phi(\epsilon_{it})}{\Phi\left(\frac{z_{it}\gamma}{\sigma_\epsilon}\right)} \ ;\ i = 1, \dots, N;\ t = 1, \dots, T.$$

From ϵ_{it} we calculate $u_{it} = \sigma_\epsilon \epsilon_{it}$.

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.

Table A.1. Descriptive statistics for variables used in estimations

State		GDP	Capital	Labor	Export	Migration	HS Education	College Education	Migration Education	Migration College Education	Migration High School Education
Alabama	mean	117530000000	123130000000	2111100	7411300000	2321	34430000	8581800	8.0090	205.4700	547.8000
	sd	13392000000	9709600000	54798	2316600000	925	85509000	21304000	0.2568	72.4740	139.4400
Alaska	mean	31106000000	32107000000	321040	2809800000	1262	3179400	950940	7.9414	230.2300	477.3800
	sd	2876900000	1591300000	18700	402200000	209	10240000	3085000	0.1865	76.2290	151.7300
Arizona	mean	156860000000	152220000000	2523400	11938000000	12883	44512000	13767000	7.7330	242.4700	504.5300
	sd	36317000000	28457000000	320760	2798100000	5085	110810000	34491000	0.1361	64.7590	93.1650
Arkansas	mean	67599000000	72453000000	1261800	2621500000	1755	11936000	2728000	7.6858	154.2100	553.1400
	sd	8647800000	6724200000	49111	660970000	725	39828000	9178700	0.1713	37.7930	70.1200
California	mean	1246200000000	1312900000000	16623000	97208000000	220890	258370000	96348000	7.6802	1682.6000	2632.0000
	sd	218670000000	190390000000	1019400	13628000000	42375	637700000	239150000	0.1820	389.3100	375.2900
Colorado	mean	158270000000	180270000000	2329300	5533900000	9308	40247000	16095000	8.5394	429.6400	571.7100
	sd	30580000000	33347000000	208280	810040000	2408	96539000	38746000	0.2401	187.5000	205.4800
Connecticut	mean	156060000000	157580000000	1777100	7899700000	11195	29945000	12157000	8.5784	352.2700	563.0000
	sd	19000000000	18407000000	34129	1416300000	2920	73982000	30216000	0.1764	200.0700	267.1000
Delaware	mean	39177000000	29497000000	406570	2119800000	1470	3894700	1185600	8.3466	223.6400	500.5700
	sd	7187200000	3152600000	22040	559500000	427	12988000	3957100	0.1870	104.5000	194.1200
District of Columbia	mean	62018000000	48211000000	306260	680880000	2817	2564900	1410900	9.3492	242.2100	311.2900
	sd	8475500000	6478400000	10922	284280000	529	8435800	4710000	0.2930	88.0710	116.6900
Florida	mean	485500000000	445890000000	7860100	25283000000	85580	147710000	44627000	8.4723	870.9300	1884.5000
	sd	96503000000	67303000000	708070	5128500000	30499	367090000	111550000	0.1784	205.1500	213.9500
Georgia	mean	271470000000	283320000000	4122100	13842000000	15961	71231000	23039000	8.0597	288.2100	624.1400
	sd	44180000000	39710000000	380700	2898600000	7566	171090000	55712000	0.1377	103.4700	180.9500
Hawaii	mean	44756000000	38581000000	610240	404790000	6652	10716000	3784600	8.5620	288.4700	541.9300
	sd	4140200000	2024900000	18950	165910000	1199	26492000	9467300	0.2639	155.1600	244.1400
Idaho	mean	34562000000	36446000000	659530	2287900000	1951	11166000	3175700	7.7110	215.8000	510.6700
	sd	6311600000	4248300000	56874	767330000	418	27755000	7952700	0.1619	57.6920	68.1070
Illinois	mean	456420000000	473030000000	6358200	28388000000	43054	99817000	34497000	8.1476	750.0000	1425.6000
	sd	51150000000	36369000000	163370	5268400000	6308	246230000	85777000	0.1338	133.1900	191.3500
Indiana	mean	187030000000	198860000000	3130100	13902000000	5216	52588000	13255000	7.9614	213.4300	712.9300
	sd	22139000000	13644000000	68595	3184000000	1548	125650000	31929000	0.1940	116.1400	244.4400
Iowa	mean	91831000000	88863000000	1609800	5109800000	3417	24620000	6694300	8.2049	274.2000	650.1300
	sd	12367000000	8626800000	30294	1299300000	1312	60716000	16589000	0.1428	123.3600	192.6000
Kansas	mean	84023000000	91100000000	1410900	4888200000	3785	21867000	7428900	8.3874	307.8000	545.6700
	sd	10251000000	10252000000	49273	1415400000	729	53884000	18418000	0.1195	121.8100	147.8300
Kentucky	mean	112230000000	119060000000	1933200	9570000000	3285	29863000	7359700	7.8980	182.4000	566.8000
	sd	11011000000	6284700000	66967	3282400000	1431	73530000	18114000	0.1671	57.5770	144.6800
Louisiana	mean	147990000000	149680000000	2001400	18687000000	3190	30593000	7799400	7.7292	173.4700	470.2700
	sd	20078000000	9620700000	49690	3005800000	570	75329000	19165000	0.2761	38.6410	87.3440
Maine	mean	35793000000	34901000000	668820	1830300000	1124	11200000	3229100	8.4771	248.4000	640.2700

	sd	4501900000	2292400000	23856	328190000	382	27602000	8033000	0.2045	132.4800	252.0600
Maryland	mean	185260000000	170530000000	2820800	5360000000	20235	45412000	18839000	8.7416	346.0000	562.4700
	sd	28717000000	28496000000	100380	932790000	4293	112100000	46345000	0.1853	191.8200	252.3300
Massachusetts	mean	254260000000	269270000000	3329700	17208000000	25558	53499000	23074000	8.7406	553.3300	861.5300
	sd	33158000000	33546000000	89316	2694000000	6560	131760000	57304000	0.1951	146.2500	295.4100
Michigan	mean	311070000000	340580000000	4990700	31751000000	17659	82141000	23237000	8.1157	526.2000	1322.9000
	sd	25922000000	23432000000	126670	2541900000	3580	202710000	57723000	0.0920	88.0070	193.5400
Minnesota	mean	179620000000	191100000000	2772900	10450000000	10599	44182000	16021000	8.4946	403.9300	587.2000
	sd	27170000000	20609000000	130390	2132900000	3656	109310000	39885000	0.1456	210.5400	204.0800
Mississippi	mean	66076000000	65911000000	1286900	2875700000	1132	20630000	5480100	7.7615	164.3300	432.0000
	sd	6546700000	4711000000	31290	686790000	335	50945000	13591000	0.1902	31.6200	60.5570
Missouri	mean	172430000000	176530000000	2915900	6551300000	6000	48800000	13935000	8.2340	248.7100	567.0000
	sd	18900000000	13055000000	96573	1906000000	1888	116600000	33289000	0.1889	106.6400	209.0300
Montana	mean	22246000000	27716000000	459700	475540000	433	505410	136970	8.2729	224.3800	473.9200
	sd	3159700000	2732500000	20313	159050000	77	42739	16604	0.1644	26.9370	50.9750
Nebraska	mean	56176000000	59160000000	938710	2262300000	2548	15508000	4493800	8.1431	272.1400	580.0000
	sd	6580400000	8461600000	35180	394000000	922	37091000	10819000	0.1681	110.1200	134.8500
Nevada	mean	74454000000	76931000000	1031800	1653300000	7588	10622000	2840100	7.9359	238.3600	666.0000
	sd	19116000000	12102000000	165280	1196400000	2507	35901000	9709600	0.2099	115.0000	264.3200
New Hampshire	mean	40851000000	43408000000	682080	1876200000	1904	12037000	4243400	8.6175	317.2100	517.2900
	sd	6209700000	6279700000	41571	453350000	827	28841000	10202000	0.1498	191.8800	259.1600
New Jersey	mean	338530000000	335080000000	4281500	16708000000	50043	70834000	29098000	8.5525	709.9300	1221.5000
	sd	42182000000	31239000000	135650	3844300000	10378	174600000	72410000	0.1376	121.0900	273.1500
New Mexico	mean	52304000000	47083000000	854550	1682300000	3435	14036000	4626900	7.7464	203.2000	531.4700
	sd	6870600000	4211100000	56672	773280000	968	34724000	11535000	0.3374	27.8850	67.9480
New York	mean	751420000000	810440000000	9126300	39714000000	126680	152920000	55779000	8.3008	1088.3000	2260.1000
	sd	92112000000	79776000000	305620	7020500000	23917	377140000	138420000	0.1055	144.1100	284.4500
North Carolina	mean	265420000000	239540000000	4081800	16132000000	10323	65610000	19793000	8.1868	452.2000	975.8700
	sd	47765000000	22611000000	270520	2011100000	4525	162800000	49304000	0.1303	63.7140	229.0200
North Dakota	mean	18092000000	20927000000	345000	781000000	535	336090	88422	8.2694	232.0000	425.6400
	sd	2380000000	2030100000	9809	324460000	122	22599	11449	0.2012	84.5480	101.1400
Ohio	mean	361340000000	360390000000	5771700	26753000000	11504	92238000	24291000	8.2118	598.6700	1564.7000
	sd	33628000000	18026000000	137510	3841600000	3287	226950000	59702000	0.1523	79.0010	227.8700
Oklahoma	mean	95128000000	124280000000	1647200	2884100000	3557	27569000	7459000	8.1093	213.9300	576.2000
	sd	13527000000	19607000000	62579	510300000	829	68037000	18475000	0.2260	41.5910	88.5250
Oregon	mean	107720000000	114780000000	1787400	9889900000	8187	30138000	9645800	8.3422	267.6700	483.1300
	sd	20037000000	12454000000	96116	1933200000	2134	74535000	23963000	0.1642	95.8430	131.7900
Pennsylvania	mean	388440000000	427740000000	6105600	17002000000	18635	101330000	40534000	8.3440	675.9300	1844.2000
	sd	41090000000	30487000000	132950	3179000000	4622	249510000	81188000	0.1586	112.8800	209.0200
Rhode Island	mean	33357000000	31179000000	542050	1137400000	2981	8777300	3131700	8.3718	268.0000	491.8600
	sd	4867300000	2980300000	20784	107770000	716	20964000	7512100	0.1781	151.4500	216.9400
South Carolina	mean	109990000000	104560000000	1946200	8832200000	2784	33949000	9528200	7.9908	201.1400	485.7100
	sd	14313000000	10045000000	83926	2263300000	1068	81401000	22942000	0.2883	76.9350	137.1100
South Dakota	mean	22249000000	20534000000	400450	558210000	546	388320	100160	8.0288	238.7300	549.1800
	sd	3395200000	2002400000	20723	253580000	157	30317	16816	0.3205	92.6220	146.1900

Tennessee	mean	173690000000	172560000000	2830200	11693000000	5438	44148000	11778000	7.9159	200.6700	542.0700
	sd	22439000000	20817000000	126260	3743100000	2291	109060000	29218000	0.2046	71.3210	101.5300
Texas	mean	734560000000	983230000000	10391000	91082000000	72585	154420000	50004000	7.4075	874.0000	1768.5000
	sd	141580000000	183210000000	730690	24303000000	17838	382360000	124350000	0.0982	198.4700	232.4800
Utah	mean	67202000000	67737000000	1143000	3947300000	4135	17634000	5431700	7.6475	252.4000	475.8000
	sd	13845000000	9604100000	124340	1126000000	985	43826000	13513000	0.2060	86.0940	108.5900
Vermont	mean	17429000000	18793000000	335600	3034700000	749	5747900	2157300	8.5798	261.0700	485.2900
	sd	2178600000	1852300000	13744	897190000	180	13725000	5193700	0.2747	131.6900	201.0100
Virginia	mean	254530000000	224930000000	3623600	11636000000	21760	63099000	22918000	8.6496	377.9300	633.2100
	sd	45125000000	33072000000	212010	1223700000	6494	150900000	54911000	0.1916	138.5900	195.6300
Washington	mean	215460000000	214370000000	3047900	34591000000	20252	52665000	23653000	8.5455	324.6000	530.4700
	sd	34906000000	30441000000	203640	7486600000	4037	130230000	47631000	0.1361	130.1300	173.8900
West Virginia	mean	42650000000	57297000000	798260	2357500000	612	15944000	3035200	8.0081	138.1400	652.0700
	sd	3603500000	3002200000	11750	461520000	143	36427000	6888600	0.2874	45.0140	166.4000
Wisconsin	mean	171360000000	175450000000	2972300	10989000000	5641	46290000	12634000	8.2190	307.9300	732.3300
	sd	21050000000	16536000000	92014	2112100000	1824	114890000	31399000	0.1672	127.8700	234.4100
Wyoming	mean	19268000000	27231000000	261500	505170000	262	276500	63783	8.0203	173.2700	463.2700
	sd	3441900000	3096400000	12442	79140000	54	18943	9083	0.2966	49.3340	141.2200

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.