On the Nexus between Innovation, Productivity, and Migration of U.S. University Graduates*

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Abstract

This paper studies the link between the migration of U.S. university graduates, innovation and productivity. Using migration flows extracted from the SESTAT database and following a simultaneous equation approach, I find that there is a positive and statistically significant relationship between the migration flows of skilled economic agents and innovation (and productivity). Higher taxation and housing prices act as a decelerating force to migration. The role of STEM graduates, potential investors, and entrepreneurial education, appear to play a salient role in regional innovation. The results are robust to various implementations, including the use of the instrumental variables approach.

JEL Classifications: J31, J61, O30, R23

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1. Introduction

The role of education in modern economies is well documented. Not only education acts as a basis for the future welfare of individuals, but it is also a stepping-stone for a country's innovation and growth capabilities. An innate characteristic of knowledge is its property to be transferred across regions, as people choose optimal locations to live and work. This indicates that the accumulated human capital of a region changes as people choose different locations during their lifetime. To this end, migration is expected to play a crucial role in shaping a region's future. This can be partially explained by the spillover effects and positive externalities surging from both individuals and firms, which are then magnified by various agglomeration forces.[1] Eventually, these spillover effects can lead to vast differences across regions, as firms may operate under increasing returns (Romer 1987; Jaffe et al. 1993).

In Economics, optimal location choices have been analyzed in growth theory (Nelson & Phelps 1966; Grossman & Helpman 1994; Glaeser et al. 1995; Vandenbussche et al. 2006), in amenity studies (Roback 1982; Roback 1988), and the New Economic Geography (NEG), popularized especially after the seminal work of Krugman (1991).[2] Recent academic work points to the direction that both economic reasons and amenities affect location choices. Biagi et al. (2011) study inter-provincial migration in Italy and find that long distance migration is a result of wage differentials, while short distance migration is triggered by differences in amenities. Mulhern and Watson (2009) try to answer the puzzle of Spanish internal migration and find that wages, unemployment, and housing prices affect migration decisions. For the case of Mexico, Flores et

[1] For studies about the United States see Jaffe (1989) and Anselin et al. (1997) among others, while for studies in Europe see Florax and Folmer (1992), Anderson et al. (2009), and Faggian and McCann (2009).
[2] For a discussion about the classical view of migration for amenity purposes and NEG see Partridge (2010).

al. (2013) find that the period after the North American Free Trade Agreement (NAFTA) saw a surge in Mexican interstate migration. Mellander et al. (2011) study people's choice to stay at their current locality and find that the beauty, physical appeal and the potential to make friends, play a vital role. Wang et al. (2016) argue that cultural diversity might increase the probability to stay in a region or migrate there; however, this is not the case for cultural distance, which appears to have the opposite effect. As for the migration of "college-bound" individuals, Faggian and Franklin (2014) show that for the case of the U.S., freshmen high-quality students prefer East- and West-coast states. This raises the question of potential future inequalities between states that can accumulate throughout the years due to human capital gaps.

Productivity and innovation are important determinants of a region's growth. Solow (1957) introduces a method to measure Total Factor Productivity (TFP) as the portion of output not explained once we account for the means of production. To measure innovation, researchers rely on proxies, such as R&D expenditures or patent counts (Griliches 1979; Jaffe 1986; Griliches 1990). Recently, other researchers point to other proxies for innovation, such as patent citations (Bloom & Reenen 2002), face-to-face contacts among people, or even cooperation among firms (McCann & Simonen 2005; Simonen & McCann 2008).

Technological advancements are strongly related to education—highly innovative locations tend to be inhabited by highly-skilled individuals. Among others, the works of Romer (1986, 1987), Lucas (1988) and Jovanovic and Rob (1989) incorporate education in growth models, while Mansfield (1991) looks at the importance of knowledge in process innovation. Bradley and Taylor (1996) document that more education increases regional growth, while others (Acs et al. 2002; Jaffe et al. 1993; Audretsch & Feldman 1996; Audretsch & Stephan 1996; Anselin

et al. 1997) argue that innovation is the result of the interaction of human capital with knowledge spillovers whose cumulative effects are more prominent in the long-run.[3]

Past research has found that producers (*i.e.*, firms) tend to cluster at specific localities (*e.g.*, Silicon Valley or Boston Route 128 in the United States, or Ruhr-Rhine in Europe). This behavior has obvious impacts in the future economic prosperity of the locality, *inter alia*. Usually regions where firms locate tend to thrive economically. Eventually spillover effects occur, as localities expand (Rauch 1993; Kelly & Hageman 1999; Carlino et al. 2007) and productivity increases (Ciccone & Peri 2006). Structural transformation that usually follows, affects the course of regional growth (see Caselli & Coleman, 2001). The above is a source of potential concerns for policy makers, since some regions may fail to adopt new technologies and be left behind.[4]

Although the extant literature in regional economics has provided material insights on regional socioeconomic disparities and their causes, the literature remains relatively silent regarding the relationship between the domestic migration of highly-skilled economic agents and a region's innovation and productivity, especially for the case of the United States.

Faggian and McCann (2009) study the migration of recent U.K. graduates and find a positive relationship between innovation and mobility. A potential intermediate channel connecting innovation and human capital mobility is through the presence of institutions of higher education. Abel and Deitz (2012) recognize that institutions providing tertiary education raise the stock of human capital. However, their analysis finds that education stock does not seem to play a significant role in a region's innovation and productivity. Importantly, Faggian and Franklin (2014) find that states with more selective institutions are able to attract first year students of higher

[3] For an empirical investigation of these hypotheses, see Moretti (2004a, 2004b).
[4] Quah (1996) studies the dynamics of inequality among different European countries. He finds that geographical factors at the regional dimension matter more than those at the national level.

quality. Winters (2013) argues that the presence of highly educated people in a region leads to positive externalities, which eventually affect also those with lower educational background. Similar results have been found in Anderson et al. (2009) and Ponds et al. (2010).

The aim of this paper is to disentangle the relationship between the migration of highly-skilled economic agents and regional innovation and productivity. In doing so, it utilizes U.S. interstate migration flows of university graduates, with data retrieved from the Scientists and Engineers Statistical Data System (henceforth SESTAT), along with other relevant variables at the regional level, to empirically test the simultaneous relationship between innovation and the migration of highly-skilled individuals.

The geographic unit of state has been chosen for a number of reasons. To start with, although the United States comprise many states within their territory, these states are dissimilar with each possessing its own distinct characteristics. For the purposes of this work, one could spot differences regarding education (e.g., the amount of funding provided for education), taxation laws for individuals and corporations, and other economic policies administered at the state level. In addition, due to its large size, the United States territory is geographically diverse and incorporates many climate types, hence providing its inhabitants different types of amenities. Finally, the country exhibits discrepancies in terms of the median income earned in each different state, but also the types of industries developed therein. Consequently, the aforesaid provide a suitable setting to study the relationship between migration, innovation, and productivity.

This work is closely related to that of Faggian and McCann (2009), although it differs in a number of dimensions. First, this paper regards migration in the United States, a country that differs markedly from the United Kingdom, both in terms of geography, economic structure, but also demographics. Second, the SESTAT database allows the researcher to concentrate on a

specific category of graduates, those with Science, Technology, Engineering, and Mathematics (STEM) degrees. Third, I utilize different measures of innovation (e.g., patents) and productivity (e.g., TFP and labor productivity). Fourth, the database employed spans for a period of 17 years, thus allowing for the use of more advanced econometric models, such as the instrumental variables approach for panel-date models.

The findings of this work indicate that innovation, productivity, and the migration of highly-skilled economic agents are positively correlated. Furthermore, the econometric results reveal that individuals favor places with lower inequality, housing prices, and taxes. In addition, innovation and productivity are positively correlated with the presence of more STEM graduates, more educated entrepreneurs, higher population density, and higher investments in R&D.

The rest of this paper is organized along the following lines. Section 2 describes a simple theoretical model of migration. Sections 3 and 4 describe the data used and the empirical design. Section 5 presents the empirical evidence. Section 6 concludes.

2. Theoretical considerations

A theoretical model of migration should be able to capture not only wage differentials as factors that determine migration choices, but also amenities and housing prices. Such a model is that of Clemente et al. (2016), presented below.

The model assumes an economy with two locations: the origin (i) and the host region (j). Economic agents live only for one period and at the very beginning of their life they choose whether to stay in location (i) or move to location (j). To do so, they compare the expected utility of the two different locations. We denote the above with U_i^e and U_j^e. Clemente et al. (2016) set the following function for total migration:

$$M_{ij} = f\left(\frac{U_j^e}{U_i^e}\right), \tag{1}$$

For eq. (1) the following holds: $\frac{\partial M_{ij}}{\partial U_j^e} > 0$ and $\frac{\partial M_{ij}}{\partial U_i^e} < 0$.

An economic agent living in region $r = \{i, j\}$ derives utility from the consumption of goods, c, and housing, s. Her utility is:

$$U_r^e = c_r^\alpha s_r^\beta, \tag{2}$$

with $\alpha, \beta > 0$.

Clemente et al. (2016) further assume that the price of consumption good is normalized to one for both the origin and host country. House prices (g) differ though and depend (positively) on the expected wage in origin and destination, as well as in amenities (a).[5]

For an expected wage w_r^e, an individual's budget constraint has the following form:

$$c_r + g_r\left(w_i^e, w_j^e, \alpha\right)s_r = w_r^e \tag{3}$$

Accounting for the budget constraint of eq. (3), the maximization of eq. (2) yields:

$$c_r = \frac{\alpha w_r^e}{\alpha+\beta}, \tag{4}$$

$$s_r = \frac{\beta w_r^e}{(\alpha+\beta) g_r(w_i^e, w_j^e, \alpha)}. \tag{5}$$

Based on these results, we deduce that when the elasticity of housing price is large enough (this happens for the case of luxury goods), an increase in wages can increase housing price up to a

[5] This means that that $\frac{\partial g_r\left(w_i^e, w_j^e, \alpha\right)}{\partial w_i^e} > 0$, $\frac{\partial g_r\left(w_i^e, w_j^e, \alpha\right)}{\partial w_j^e} > 0$, and $\frac{\partial g_r\left(w_i^e, w_j^e, \alpha\right)}{\partial \alpha} > 0$.

level that will result in a decrease in utility. Therefore, this model stresses the importance of accounting not only for wages, but also for housing prices and amenities, in people's decision to migrate. [6]

3. Data

To measure the migration flows of highly educated individuals, I use information from the Scientists and Engineers Statistical Data System (SESTAT) obtained from the National Science Foundation (NSF) under a specific agreement. This database is a combination of three additional surveys: (i) The National Survey of College Graduates (NSCG), (ii) The National Survey of Recent College Graduates (NSRCG), and (iii) The Survey of Doctorate Recipients (SDR). Starting 1970, the surveys have been conducted in a biennial basis and gather information for individuals who are residents of the United States and have been awarded at least a bachelor's degree in science or engineering.[7] This database contains a plethora of information at the individual level, such as age, the various levels of education, degrees and majors chosen, a person's occupation, and annual salary. Importantly, through this database one can find the locations of all states where degrees were awarded. Furthermore, SESTAT includes information on the state an individual was employed at the time the survey took place. In a recent study, Kazakis and Faggian (2017) use this database and find a positive relationship between repeat migration and labor market outcomes, while dealing with the issue of selectivity.

[6] Other parameters that might affect people's movements are regional dynamics (e.g., Partridge et al., 2008). The authors argue that it is possible for migration flows to be sustained when regional conditions are characterized by continuous changes. Such conditions are, *inter alia*, changes in income—an increase in income increases the demand for natural amenities, a normal good (Graves 1980; Blanchard et al. 1992)—or changes in transportation or communication (Partridge et al., 2010). Other factors that affect migration are business cycles (Saks & Wozniak, 2011).

[7] In this study, I use information for the years: 1993, 1995, 1997, 1999, 2003, 2006, 2008, and 2010.

The first important component of this analysis is to find proper proxies for innovation and productivity. By definition, innovation encompasses new ideas or methods, or the use of new ideas and methods.[8] Following the extant literature on innovation, I utilize patents as my main proxy. Patent information have been retrieved from the USPTO (United States Patent and Trademark Office) website. The USTPO provides electronic files that contain information (including regional characteristics) about inventors and assignees (people or businesses who can acquire an ownership interest in a patent application by assignment from the inventor). To determine the location of a patent, I utilize information from the descriptions provided therein, whereby in most cases the full name of a state or its abbreviation are recorded. Through this, I pin down the number of patents for each state and period studied.

Apart from innovation proxies, I calculate productivity proxies, such as total factor productivity (TFP) and labor productivity per hour. To calculate TFP, I follow the insights of Garofalo and Yamarik (2002). First, I gather time series data for capital stock at the state level using data from the Bureau of Economic Analysis (BEA).[9] Once capital for each state and industry is found, I apply the following formula: $k_{m,n}(t) = \left[\frac{y_{m,n}(t),}{Y_m(t)}\right] K_m(t)$, with $k_n(t) = \sum_{m=1}^{M} k_{m,n}(t)$. Subscript m is used for industries and n for states. Capital letters denote total values for each industry at the country level. As for labor productivity per hour, this is calculated at the state level as $\frac{GDP}{L(x)H}$, where L denotes the number of workers in a state and H the average hours worked at that state.

The second main component of this analysis is the additional potential knowledge (human capital) entering a region as individuals move. In this work, human capital is measured

[8] Definition taken from Cambridge dictionary.
[9] I calculate capital stock for the following industries: farming, agricultural services, forestry, fishing & other, mining, construction, manufacturing, transportation, wholesale and retail trade, finance, insurance, real estate, services).

using the migration flows of highly-skilled economic agents. That is, the number of university graduates who are employed at a state different from the one they were born at the time the SESTAT questionnaire took place. Next, I proceed with a short discussion regarding the main controls used in this work.

I measure density based on counties that comprise around 75% of a state's population using data from the U.S. Census Bureau.[10] I obtain information about inequality from Mark W. Frank's database.[11] I use air quality data from EPA as a proxy for amenities. In addition, I include a home price index to account for potential real estate investment possibilities. These data are taken from the FHFA & Lincoln Institute of Land Policy. Personal taxation is a factor that could affect migration decisions, whereby individuals would prefer regions with lower taxation, *ceteris paribus*. To this end, I obtain average state personal tax information from the BEA. To account for patent inputs, I utilize academic R&D expenditures with data from the NSF. From IPUMS (CPS), I calculate the average educational level of entrepreneurs, while from the SESTAT the ratio of population with a STEM degree in each state. The idea is that STEM graduates possess very technical skills that are a crucial ingredient for innovation and productivity enhancements.[12] Information about the variables used can be found in Table 1 below.

[Insert Table 1 about here]

[10] Counties are chosen starting from the most populous to the least populous until the 75% population threshold is reached.

[11] The author has constructed the database from individual tax filling data provided from the Internal Revenue Service (IRS). The data can be found at: http://www.shsu.edu/eco_mwf/inequality.html.

[12] More information about the values of the variables by state can be found in the Online Appendix. In brief, Table A1 indicates that California produces most patents in the nation. This is not a surprise, as the latter has become the center of innovation, especially in transistor technologies and electronics. TFP calculation also ranks California first. Table A2 shows California to be first in the number of high-tech firms (absolute number) and fourth in per capita terms, immediately after Massachusetts, Connecticut, and New Jersey. Table A3 has more information on home price indices, air quality index, entrepreneur's education, academic R&D expenditures, and per capita taxation by state. Major choice rankings for domestic graduates and graduate immigrants for the five most innovate and least innovative states are found in Tables A4 and A5. Generally, most innovative states attract graduates from hard sciences (e.g., electronics, physics, and chemistry).

Summary statistics are found in Table 2. Further inspection of summary statistics reveals substantial differences among states. For example, the most innovative states document up to 4.4 times more per capita patents compared to their counterparts. In the same manner, TFP may differ up to 2.7 times. Furthermore, the U.S. tend to have a high level of inequality, as shown by the Gini coefficient. The average (unweighted) Gini coefficient is about 58% and the top 1% richest people possess, on average, 16% of a state's income.[13]

The United States document significant heterogeneities regarding their demographics and economic activity at the state level. For example, population density spans from 771 inhabitants per square mile to 9,864 inhabitants per square mile.[14] Data reveal that about 20% of graduates in a state possess a STEM degree. On average, there are about 63,577 ($= e^{11.06}$) firms that employ up to 20 employees. The average entrepreneur holds a high school degree, with some of them having college experience. As for amenities, air quality index[15] has an average value of 47, ranging from 11 to 127.[16] The average home price index is 1.17, with the lowest values found in Michigan, while the highest in Hawaii. Furthermore, we observe large differences in the per capita academic R&D expenditures (the highest levels are observed in DC, Maryland, and Massachusetts, while the lowest values are observed in Maine, West Virginia and Arkansas). Finally, we also find large differences in per capita taxation across the country (highest taxation is found in Alaska and lowest in Oregon).

[13] Individual data from IRS for the period 2010-2014 reveal that the Top 1% owned around 38% of the U.S. wealth. This cannot be seen in this database because an aggregate measure has been used. For example, the data for the top income states show that the inequality is higher, accompanied with higher income gaps (wealth is more polarized).

[14] This number is calculated based on the largest counties that consist 75% of a state's total population. I follow this scheme to account for potential measurement bias due to a state's area.

[15] An index that reports daily air quality and takes into consideration four major pollutants: O3, particle pollution, CO, and SO2. The higher its value, the worse air quality is. To be more precise the EPA gives the following 6 scales: [0-50]: good; [51-100]: moderate; [101-150]: unhealthy for sensitive groups; [151-200]: unhealthy; [201-300]: very unhealthy; [301-500]: hazardous.

[16] The highest value is for Montana in 1993. The worse states in terms of air quality are: California, Arizona, Montana, Illinois, and Texas.

[Insert Table 2 about here]

4. Empirical design

Since human capital is a necessary ingredient for production of final and intermediate good products, one contends that there should be a positive relationship between the migration of highly-skilled individuals to a region and the level of productivity and innovation in that region. The idea is that, as people move, they carry with them the necessary knowledge that is crucial to further augment the innovation and productivity of a locality. At the same time, some regions have become the centers of innovation and productivity by accumulating a significant mass of knowledge in the past years, along with more efficient practices and infrastructure (e.g., Silicon Valley). These centers of excellence may act as magnets that attract professionals. That is, people may choose to migrate to a region because there they can find a job that is more compatible with their abilities and technical expertise. Furthermore, by working in a location that employs the best professionals in a field, they further improve their human capital and network. Consequently, it is rather difficult to find a dominant causal path between the migration of the highly-skilled economic agents and innovation (and productivity) in a region. For this reason, the main econometric approach used in this analysis relies on estimating simultaneous equation models, such as two-stage least squares (2SLS) and three-stage least squares (3SLS).

The main difference between the two models is that 2SLS yields inefficient estimates when the error terms are correlated. Therefore, as we are agnostic about the existence or non-existence of such correlation, we present results from both models. In addition, another reason to exhibit results from a 3SLS model is because the additional information contained in the error terms might be more useful for inference, since the 2SLS model does not utilize this additional information. In

mathematical terms, the simultaneous equation models (3SLS and 2SLS) are of the following form:

$$Ln(HK\ graduates)_j = \alpha_0 + \alpha_1 InnProd_j + \alpha_2 Dens_j + \alpha_3 Gini_j + \alpha_4 AQI_j + \alpha_5 HPI_j + \alpha_6 Tax_j + u_j \quad (6)$$

$$InnProd_j = \beta_0 + \beta_1 Ln(HK\ graduates)_j + \beta_2 [STEM(x)Top1]_j + \beta_3 Dens_j + \beta_4 (R\&D)_j + \\ + \beta_5 EducEntrep_j + \epsilon_j. \quad (7)$$

In these equations $Ln(HK\ graduates)$ denotes the natural logarithm of the highly-skilled immigration flows to a specific state. The variable $InnProd$ denotes the various innovation and productivity proxies used in the analysis. Specifically, I use as different proxies for innovation the raw number of patents per state and the number of patents per 100,000 inhabitants, while productivity proxies include labor productivity per hour, and TFP. Variable $Dens$ shows the density of the largest counties that comprise around ¾ of a state's population.[17] $Gini$ measures income dispersion, while AQI is the air quality index. HPI denotes the home-price index. $EducEntrep$ denotes the average education of the entrepreneurs in a state.[18] Tax denotes the average state taxes of a basic household basket (including groceries, gas etc.). $R\&D$ indicates the per capita university research and development expenditures. [$STEM\ (x)\ Top1$] is the product of the ratio of the population with a STEM degree and $Top1$, the share of the wealth owned by those belonging in the top 1% of the income distribution.

The previous analysis treated both migration flows and the innovation or productivity of a region as endogenous variables. In what follows I depart from this approach and I study one direction of causality. Specifically, I assume that the direction of causality runs from regional

[17] I do this in order to get an unbiased measure for density. For example, a state might be quite large and innovation might be taking place in some large urban areas. However, if we were to measure density based on the whole area of a state, this could potentially bias the measure and thus not show its true effect.

[18] Notice, however, that I do not utilize this variable in all models. This is because, in many occasions, observations regarding entrepreneurial education are missing.

innovation and productivity to the migration of highly-skilled. The idea stems from the fact that some regions have become the centers of innovation and productivity and as they expand, they continuously attract talent. Such examples are the Silicon Valley in California, Boston, or Tokyo, which have been traditionally among the most important sources of innovation. These are exactly the places where a large number of young and ambitious individuals choose to migrate. Another advantage of using the IV approach is that it serves as a tool to further reduce bias that is common in simultaneous equation models.

Developments in innovation and productivity require new and bold ideas. Usually these ideas come from individuals with specific technical skills. For example, on average firms employing graduates with STEM degrees are more likely to file for high quality patents. Another crucial component is people who are willing to invest the necessary amount of capital to fund new ideas (e.g., venture capitalists). Consequently, the higher the number of wealthy people in a region, the more likely for its young entrepreneurs to be funded (especially startup enterprises). The latter are an important ingredient for a region's progress, as past literature finds startups to be more likely to innovate.[19] Taking this into account, I assume that a region's productivity and innovation are partially determined by the following three factors: (i) the ratio of the population with STEM degrees, (ii) the percentage of wealth held by top earners (*Top1*), and (iii) the number of firms with up to 20 employees (i.e., small firms). These variables are not expected to exert any influence in individuals' migration decisions *per se*. However, as I argued above, they are expected to influence a region's productivity. I employ these instruments one at a time.

The econometric model of the instrumental variables approach used is the following:

$$Ln(HK\ graduates)_{jt} = \gamma_0 + \gamma_1 Dens_{jt} + \gamma_2 AQI_{jt} + \gamma_3 HPI_{jt} + \gamma_4 Tax_{jt} + \gamma_5 \widehat{InnProd}_{jt} + \mu_{jt} \quad (8)$$

[19] Previous research has shown that smaller firms and startups are dominant in innovation activities in certain industries (Acs et al. 1994; Acs & Audretsch 1988).

$$InnProd_{jt} = \delta_0 + \delta_1 \cdot IV_{jt} + \boldsymbol{\delta}_2 \cdot \boldsymbol{\Xi}_{\mathbf{jt}} + \nu_{jt}, \quad (9)$$

where IV is either $STEM, Top1$, or $Firms20$. A two-stage least squares within estimator for panel data is applied in this case. Equation 9 represents a precise projection of the endogenous variable in all exogenous variables. That is, vector $\boldsymbol{\Xi}$ contains all the exogenous controls of equation (8). This allows the model to be identified.[20]

5. Results

Results of the 3SLS models are found in Table 3 and are presented in eight columns based on the different proxies used for innovation and productivity. For columns (1) and (5) the proxy for innovation is the natural logarithm of patents per 100,000. For columns (2) and (6) the proxy for innovation is the number of patents per assignee (in logs). For columns (3) and (7) the productivity proxy is labor productivity per hour, while for columns (4) and (8) the productivity proxy is total factor productivity (TFP) calculated in the manner discussed in section three. Columns (5) to (8) differ in that they additionally contain the average entrepreneurial education at the state level as a control.

[Insert Table 3 about here]

Upon inspection, the results from Table 3 indicate that all proxies used for innovation and productivity enter with a positive coefficient, which is statistically significant in 7/8 cases. Coefficient values range from 0.519 (for the case of labor productivity) to 0.966 (for the case of patents per 100,000 inhabitants). This indicates that there is a positive correlation between the levels of innovation and productivity in a state and the migration inflows of highly qualified

[20] To avoid multi-collinearity issues (i.e., between *Top1* and *Gini* variables), I do not include the $Gini$ coefficient in the IV models.

individuals in that state—economic agents prefer more innovative and more productive areas to work and live.

Past economic literature has found that individuals, especially younger cohorts, prefer larger and denser areas (see Chen & Rosenthal 2008; Storper & Scott 2009). Some reasons for this include better job matching perspectives and the amenities larger urban areas offer, *inter alia.* The results from the 3SLS method indicate a possible positive relationship. However, the coefficient is insignificant.

Next, I investigate the relationship between inequality (as proxied by the Gini coefficient) and highly-skilled migration inflows. The results do not provide a decisive answer regarding the direction of the effect. When the dependent variable is a proxy for innovation (columns 1, 2, 5, and 6), coefficients enter negatively and are statistically significant in ¾ cases. When the dependent variables are proxies for productivity the coefficient is positive, but statistically significant in only the case where the dependent variable is TFP. Notice though, that this could be due to power issues, as the sample is almost halved when entrepreneur's education is included in the econometric analysis. These results, could indicate that highly-skilled people might prefer locations with higher inequality, as they are more likely to belong to the right tail of the income distribution owing to their higher paid jobs, a result of the skills they possess. That is, in locations where highly-skilled economic agents are paid their marginal productivity, it is more likely to see higher income inequality. It is expected that this effect would be smaller if the analysis was conducted at a smaller regional level (e.g., when highly-skilled economic agents move between relatively wealthy neighborhoods).

The findings of Table 3 illustrate that graduates tend to sort to places with relatively lower level of air quality (higher AQI). This result, although surprising at first, may hint that areas where

graduates can find more remunerative jobs relevant to their abilities are usually located in regions where economic activity, and thus pollution, is more pronounced.[21]

A crucial factor that determines migration decisions is housing prices in the new location. The higher the housing prices in the new location, the less likely for individuals to migrate there. The results obtained pinpoint to this direction. The home-price index coefficient enters with a negative and statistically significant value in all cases, but the last regression model (column 8). Another potential cost individuals may have to face when changing a location stems from tax differences. We expect that when taxation in a region is high, people will be more reluctant to migrate there. The econometric analysis yields mixed results. In most cases the coefficient is negative, but statistically significant in half of the cases studied. There is one case (when the dependent variable is TFP), where the coefficient is positive and statistically significant at the 5% level.[22]

I proceed with the results of the second equation of the simultaneous equation model. We are mainly interested to see how the migration of highly-skilled economic agents in a region affects the innovation and productivity in that region. So far, we have hypothesized that human capital migration should increase the innovation and productivity of a region. The results we obtain (see the coefficient for $Ln(HK\ graduates)$) indicate that there is a positive relationship, albeit not statistically significant in all cases. In fact, there are two occasions where we obtain a negative coefficient—when the dependent variable is labor productivity per hour. The calculation of labor productivity utilizes wages at the state level. Thus, the negative coefficient may indicate potential demand and supply forces at work, whereby the number of graduates in a region increases more

[21] When including the USDA amenity score instead of the air quality index, a positive relationship was found. Results available on request.
[22] The coefficient for tax per capita is negative and statistically significant (in most cases) in the 2SLS simultaneous equation approach and in the instrumental variables models.

than the number of jobs, thus setting lower wages in equilibrium. Notice that the results of the 2SLS estimation (Table 4), show either no effect in this case, or have a positive coefficient.

As it was argued before, the presence of potential investors (captured via $Top1$) and graduates with STEM degrees, are an important ingredient for innovation and productivity enhancements. To capture this, I utilize an interaction term of the above. The results indicate a very strong and statistically significant relationship in all but one case. One could perceive this as a first-hand evidence of the positive role potential venture capitalists have in innovation. Their role is enhanced by the presence of people with the "right" type of degrees. Thus, the role of potential entrepreneurs appears to be more decisive when it is combined with higher levels of human capital and people with specialized knowledge, such that of STEM graduates.

In the first equation of the simultaneous equation model (3SLS), we found a weak positive relationship between density and migration inflows. I include density in the second equation of the simultaneous equation model (3SLS) as well. The reason lies on the role population density plays in agglomeration and human networks. Simply put, (positive) externalities can travel faster in denser environments. The results reveal a strong positive and statistically significant relationship between density and the proxies for innovation and productivity: denser regions are more likely to innovate and have higher levels of productivity.

Next, I control for the academic expenditures in R&D to further study the role of inputs in innovation and productivity enhancements. This is because past research has documented a positive role university and other research centers have in knowledge creation. As expected, we find a strong and statistically significant positive relationship in most of models, except the one presented in column (8) where the dependent variable is TFP. As mentioned before, a reason for this could be the smaller sample. Columns (5) to (8) show results including the average education

of entrepreneurs. Based on human capital theory, we should expect a positive relationship between entrepreneur's education and innovation. A reason for this is that people with higher education possess skills that let them process information better and faster compared to the others. In three out of four cases we find a positive and statistically significant coefficient. However, a negative coefficient is present when the dependent variable is TFP.

As Wooldridge (2010) points out, there are tradeoffs in the choice between 2SLS and 3SLS models. If all equations in a system are correctly specified, the 3SLS approach is asymptotically more efficient. However, in the case of misspecifications, then the 3SLS method might yield inconsistent estimates. To this end and for comparison, I present 2SLS results in Table 4. Juxtaposing the results of the 3SLS model to those of the 2SLS model, I find that the 2SLS estimation tends to produce more significant coefficients. Specifically, for the variables that we are interested in (migration of highly skilled economic agents and innovation or productivity proxies), the results show a strong and positive relationship in most cases, thus confirming once again what we have hypothesized so far in the analysis.

[Insert Table 4 about here]

Based on the arguments presented in the previous sections, I concentrate in one direction of causality, whereby innovation or productivity drive the migration flows of the highly-skilled. Table 5 presents results where variable $STEM$ acts as an instrument for the various innovation and productivity proxies. Once again, the results confirm the strong positive relationship between innovation (and productivity) measures and the migration of highly-skilled economic agents. Regarding the validity of instruments, first-stage F-statistics enter with values well above the Stock and Yogo (2005) thresholds in most of the cases.[23]

[23] Instrumental variables approach outcomes for $Top1$ and $F20$ are presented in the Online Appendix Tables B1 and B2. For the case of $Top1$, the first stage indicates a strong F-statistic (except for the case where the dependent variable

[Insert Table 5 about here]

6. Conclusion

In this work I study the relationship between the migration of highly-skilled economic agents, innovation and productivity, utilizing data from the United States. To do so, I apply a simultaneous equation approach. This is the preferred method, as the causality between the highly-skilled migration inflows and innovation (or productivity) is not obvious. The results found here indicate a positive relationship between innovation (or productivity) and the inflow of highly-skilled individuals. Thus, more innovative and productive regions are more likely to attract human capital. At the same time, regions that attract more human capital, tend to be more innovative and show higher levels of productivity. From this analysis we further find that individuals favor places with lower inequality, housing prices, and taxes. In addition, the innovation and productivity levels of a region increase with the presence of more STEM graduates, the presence of more educated entrepreneurs, and higher expenditures in educational R&D. The main results survive a number of additional robustness tests and an instrumental variables approach.

The results of this analysis rely on two main methods: structural equation models (2SLS/3SLS) and the instrumental variables approach utilizing data at the state level. For this reason, a number of caveats apply to the findings provided in this work. First, one could argue

is TFP), nonetheless the main coefficient of interest ($\widehat{InnProd}$), although positive, is insignificant. When the instrumental variable is $Firms20$, the F-statistic is strong in only half of the models. Even with that outcome, the coefficient of interest enters with the expected positive sign, which is also statistically significant for 2 out of 4 models. Furthermore, I try the following interaction terms to act as instruments: $STEM(x)Top1$ and $STEM(x)Firms20$ (found it Tables B3 and B4). In both cases, I obtain results with the expected sign, which are also statistically significant, except when the dependent variable is TFP, where the results is insignificant. This suggests that although capital might be important for innovation, it needs to be combined with other factors to exert its full potential. Finally, to examine whether the results of my database hold for the population, I use the population of the destination state as a weight in my econometric models. Results are found in Appendix tables B5, B6, and B7. If anything, the findings are very close to the unweighted cases, if not stronger.

that the use of state as the unit of analysis could be too large to capture the finer nuances of the relationship in question. It is very likely that some sub-regions within a state will be affected more than others. As a result, the findings of this work regard average effects for the whole state. It would be very interesting for future researchers to study this phenomenon at a smaller scale, such as metropolitan statistical areas, or even neighborhoods.

The numerous articles published throughout the years indicate that human capital is a vital determinant of growth. This applies not only to countries, but also regions within a country. If some regions specialize in industries that can attract only low-skilled individuals, then the gap with their counterparts that attract, among others, high-type economic agents, will widen. It is therefore pivotal for policy makers to create the necessary conditions for industries to attract high-skilled human capital too. This might require generous investments that favor the altering of existing industries, or creating new ones. Research has also shown that the most bright and innovative individuals attend universities of the highest quality (and usually stay there to live and work after they finish their studies). This suggests that policy makers should try to invest in the infrastructure and quality of their schools and universities. Educational institutions of higher quality are expected to have a positive effect for a region by retaining the brightest minds (i.e., avoid "brain drain"), but also attract talent from elsewhere (i.e., "brain-gain"). Furthermore, since STEM majors appear to be an important component of innovation and productivity enhancements, a suggestion for policy makers would be to support those majors more. Another reason for this type of investment to happen, is that people with high skills are willing to move long distances to find a job relevant to their educational background.

This work found a positive relationship between the migration of highly skilled individuals and innovation. As a suggestion, future researchers should look at finer microeconomic data and

investigate how high skilled migration affects the innovation capabilities of smaller localities, but also try to answer new questions, such as how the migration of human capital affects the dynamics of inequality within a region. The author trusts that future research, with the use of better (and finer) data, will shed some light on the aforesaid, but also utilize more advanced tools to study causality and find more precise estimates.

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Table 1: Variable's explanation and data sources

Variable name	Variable meaning	Source
Ln (patents per 100,000)	The natural logarithm of patents per 100,000 individuals.	USPTO
TFP	The Solow residual calculated according to the way introduced by Garofalo and Yamarik (2002).	Own calculation (BEA data used)
Labor productivity per capita-hour	The ratio of GDP to the population-hours worked (average labor productivity).	BEA/CPS
Density (*Dens*)	The average density of the counties that consist the 75% population of a state.	U.S. Census Bureau
Gini	A coefficient that measures income dispersion—zero expresses total equality, while one total inequality—through the area between the Lorenz curve and the line of 45 degrees. For a given Lorenz curve, L(X), the Gini is: $1 - 2\int_0^1 L(X)dX$.	Mark W. Frank's database.
Top 1%	The share of the total income of a state owned by individuals who belong to the top 1% of income distribution.	Mark W. Frank's database.
Air Quality Index (*AQI*)	The mean air quality by state. This index is comprised in six classes: 0-50 (good), 51-100 (moderate), 101-150 (unhealthy for sensitive groups), 151-200 (unhealthy), 201-300 (very unhealthy), and 301-500 (hazardous).	EPA
Home Price Index (*HPI*)	A weighted, repeat-sales index that measures the change of single-family house prices.	FHFA & Lincoln Institute of Land Policy
Ln(HK graduates)	Represents the natural logarithm of the number of highly-skilled individuals who were born in some state in the U.S. and have migrated to another state to live and work.	Own calculation based on SESTAT
Tax per capita (*Tax*)	Personal income tax data (including groceries, gas etc.) Raw data are in thousands of dollars.	BEA
STEM	Ratio of population with STEM degree.	Own calculation based on SESTAT
Entrepreneur's education (*EducEntrep*)	The average educational level of entrepreneurs. This is a categorical variable with [1] indicating no high school, [2] indicating high school degree, [3] indicating some college, but not degree, [4] indicating college degree, and [5] indicating a graduate degree.	IPUMS-CPS
R&D per capita (*R&D*)	The per capita amount of academic R&D expenditures by state. Raw academic R&D expenditure data are in thousands of dollars.	NSF
Firms20	The number of firms up to 20 employees.	SUSB

NOTES: BEA-Bureau of Economic Analysis; NBER-National Bureau of Economic Research; (http://www.nber.org/patents/); FHFA-Federal Housing Finance Agency; Kauffman-Ewing Marion Kauffman Foundation; SESTAT-Scientists and Engineers Statistical Data System; SUSB-Statistics of U.S. Business (http://www.census.gov/econ/susb/historical_data.html).

Table 2: Summary statistics

Variable	Obs.	Mean	Std.Dev.	Min	Max
Ln (patents per 100,000)	408	4.33	1.09	1.74	7.61
Ln(HK graduates)	408	5.45	0.96	3.18	7.56
TFP	306	10.33	2.30	5.97	15.91
Labor productivity per capita-hour	306	9.75e-4	3.62e-4	5.55e-4	3.52e-3
Density	408	771.38	1394.04	28.85	9864.31
Gini coefficient	408	0.58	0.04	0.52	0.71
Top 1%	408	0.16	0.04	0.10	0.28
Air Quality Index	408	47.33	15.57	11.00	127.00
Home Price Index	408	1.17	0.28	0.75	2.33
Tax per capita	408	21.14	10.93	13.24	148.46
STEM	408	0.21	0.05	0.09	0.43
Entrepreneur's average education	204	2.91	0.26	2.19	3.91
R&D per capita	408	0.13	0.09	0.02	0.71
# firms up to 20 employees (in logs)	357	11.06	0.95	9.38	13.37

Notes: HK denotes highly-skilled. Average values for the years 1993, 1995, 1997, 1999, 2003, 2006, 2008, and 2010.

Table 3: Three Stage Least Squares Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equation 1: the dependent variable is highly-skilled migration to the state								
InnProd	0.966***	0.534***	0.581***	0.186	0.780***	0.553***	0.519***	0.570***
	(0.158)	(0.061)	(0.133)	(0.186)	(0.167)	(0.072)	(0.123)	(0.156)
Density	0.041	0.042	0.126	0.316	0.146	0.002	0.170	-0.135
	(0.123)	(0.081)	(0.149)	(0.266)	(0.126)	(0.093)	(0.141)	(0.220)
Gini	-2.965**	-2.425***	1.743	3.512*	-1.232	-1.006*	2.281	-0.739
	(1.354)	(0.578)	(1.828)	(1.915)	(1.610)	(0.532)	(1.966)	(1.626)
Air quality index	0.016***	0.010***	0.020***	0.034**	0.028***	0.010**	0.032***	-0.012
	(0.003)	(0.002)	(0.004)	(0.014)	(0.005)	(0.004)	(0.005)	(0.015)
Home-price index	-0.814***	-0.461***	-0.840***	-0.497	-0.511*	-0.138*	-0.741**	0.133
	(0.184)	(0.085)	(0.260)	(0.305)	(0.270)	(0.075)	(0.319)	(0.321)
Tax per capita	-0.014*	-0.007**	-0.080***	0.024**	-0.007	0.000	-0.065***	-0.000
	(0.008)	(0.003)	(0.022)	(0.011)	(0.009)	(0.003)	(0.021)	(0.011)
Constant	3.529***	2.855***	1.238	-0.496	1.973*	1.071**	0.268	0.164
	(0.972)	(0.457)	(1.247)	(0.967)	(1.113)	(0.538)	(1.365)	(1.050)
Equation 2: the dependent variables are the different proxies for innovation or productivity								
Controls\Dependent variables	Ln(patents) per 100,000	Ln(patents)	Labor productivity	TFP	Ln(patents) per 100,000	Ln(patents)	Labor productivity	TFP
Ln (HK graduates)	0.151*	0.886***	-0.910***	1.787***	0.125	1.251***	-0.985***	2.286***
	(0.088)	(0.094)	(0.198)	(0.140)	(0.138)	(0.132)	(0.257)	(0.132)
STEM (x) Top1	23.413***	29.235***	63.529***	10.243*	21.985***	12.826***	57.044***	-1.043
	(3.521)	(3.741)	(8.445)	(5.949)	(5.240)	(4.561)	(10.586)	(5.296)
Density	0.494***	0.520***	1.586***	0.247**	0.343***	0.259**	1.307***	0.145
	(0.083)	(0.088)	(0.183)	(0.123)	(0.120)	(0.110)	(0.225)	(0.113)
Ln (R&D capita)	0.328***	0.292***	1.172***	0.018	0.375***	0.104	1.157***	-0.689***
	(0.064)	(0.057)	(0.185)	(0.100)	(0.139)	(0.076)	(0.308)	(0.137)
Entrepreneur's average education					0.940***	0.354***	2.368***	-0.764***
					(0.251)	(0.161)	(0.560)	(0.255)
Constant	3.078***	2.342***	13.195***	0.299	0.776	0.061	7.127***	-0.684
	(0.428)	(0.460)	(1.003)	(0.687)	(0.884)	(0.622)	(1.965)	(0.919)
N	384	384	288	288	192	192	192	192
χ^2 for equation 1	224.74	717.84	140.64	222.59	144.15	465.71	114.05	150.35
R^2 for equation 1	0.098	0.751	0.134	0.557	0.289	0.763	0.215	0.734
χ^2 for equation 2	241.59	637.55	253.00	501.78	123.20	395.17	145.53	656.53
R^2 for equation 2	0.397	0.726	0.389	0795	0.404	0.773	0.345	0.879

NOTES: The variable representing density is computed based on regions consisting about 75% of the states' whole population (starting from the most populous region to the least populous). Columns (1) to (8) have the following proxies for innovation or productivity (InnProd): columns (1) and (5) the natural logarithm of patents per 100,000; columns (2) and (6) the raw natural logarithm of patents; columns (3) and (7) the labor productivity per hour; columns (4) and (8) the total factor productivity (TFP). Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All regressions have been tested for identification through the order and rank condition and pass the test. Significance levels: *** 1%, ** 5%, * 10%.

Table 4: Two Stage Least Squares Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equation 1: the dependent variable is highly-skilled migration to the state								
InnProd	0.731***	0.672***	0.301***	0.833***	0.725***	0.572***	0.389***	0.649***
	(0.112)	(0.059)	(0.067)	(0.125)	(0.113)	(0.051)	(0.065)	(0.078)
Density	0.174***	0.003	0.216***	-0.261**	0.171**	0.076	0.061	-0.109
	(0.067)	(0.052)	(0.081)	(0.126)	(0.078)	(0.050)	(0.089)	(0.080)
Gini	4.324***	-0.485	2.671**	-9.895***	3.956***	0.055	2.827*	-6.388***
	(1.173)	(0.759)	(1.274)	(2.273)	(1.489)	(0.826)	(1.476)	(1.372)
Air quality index	0.014***	-0.004	0.023***	-0.032***	0.018***	0.001	0.024***	-0.021***
	(0.003)	(0.003)	(0.003)	(0.009)	(0.004)	(0.003)	(0.004)	(0.007)
Home-price index	-0.409***	-0.218**	-0.283*	0.150	-0.088	-0.002	-0.042	0.169
	(0.138)	(0.091)	(0.159)	(0.178)	(0.183)	(0.106)	-0.186	(0.138)
Tax per capita	-0.031***	-0.042***	-0.028**	-0.051***	-0.015	-0.025***	-0.020	-0.035***
	(0.009)	(0.006)	(0.012)	(0.013)	(0.012)	(0.008)	(0.013)	(0.011)
Constant	0.665	1.978***	1.401*	4.935***	-0.391	1.358***	-0.180	3.892***
	(0.703)	(0.394)	(0.750)	(0.813)	(0.882)	(0.469)	(0.898)	(0.641)
Equation 2: the dependent variables are the different proxies for innovation or productivity								
Controls\Dependent variables	Ln(patents) per 100,000	Ln(patents)	Labor productivity	TFP	Ln(patents) per 100,000	Ln(patents)	Labor productivity	TFP
Ln (HK graduates)	0.429***	1.281***	0.022	2.040***	0.548***	1.787***	0.422*	2.786***
	(0.076)	(0.086)	(0.153)	(0.163)	(0.162)	(0.171)	(0.249)	(0.187)
STEM (x) Top1	12.646***	26.353***	52.559***	24.574***	12.693*	10.237	31.163***	0.167
	(3.783)	(4.330)	(7.234)	(7.901)	(6.635)	(7.005)	(10.211)	(7.678)
Density	0.229***	0.148***	0.923***	0.053	0.128*	0.087	0.666***	0.072
	(0.048)	(0.055)	(0.092)	(0.085)	(0.077)	(0.081)	(0.119)	(0.089)
Ln (R&D capita)	0.594***	0.588***	1.564***	0.083	0.585***	0.060	1.249***	-1.059***
	(0.067)	(0.077)	(0.133)	(0.132)	(0.157)	(0.166)	(0.242)	(0.182)
Entrepreneur's average education					0.267	-0.323	1.646***	-0.691*
					(0.327)	(0.345)	(0.503)	(0.378)
Constant	2.597***	1.269***	9.728***	-0.987	1.182	-0.905	3.042**	-4.295***
	(0.406)	(0.465)	(0.810)	(0.850)	(0.870)	(0.918)	(1.339)	(1.007)
N	384	384	288	288	192	192	192	192
R^2 for equation 1	0.435	0.751	0.400	0.208	0.436	0.799	0.406	0.642
R^2 for equation 2	0.512	0.788	0.661	0.813	0.482	0.792	0.630	0.873

NOTES: The variable representing density is computed based on regions consisting about 75% of the states' whole population (starting from the most populous region to the least populous). Columns (1) to (8) have the following proxies for innovation or productivity (InnProd): columns (1) and (5) the natural logarithm of patents per 100,000; columns (2) and (6) the raw natural logarithm of patents; columns (3) and (7) the labor productivity per hour; columns (4) and (8) the total factor productivity (TFP). Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All regressions have been tested for identification through the order and rank condition and pass the test. Significance levels: *** 1%, ** 5%, * 10%.

Table 5 : Instrumental variables approach with *STEM* as instrument

	[1]	[2]	[3]	[4]
Panel A: Main results				
$\widehat{InnProd}$	0.523***	0.538***	0.400***	-22.79
	(0.087)	(0.093)	(0.090)	(64.240)
Density	-0. 049	-0.0893	-0.570**	1.540
	(0.110)	(0.120)	(0.220)	(5.390)
Air quality index	-0.001	-0.001	-0.002	0.009
	(0.001)	(0.001)	(0.002)	(0.041)
Home price index	-0.428***	-0.502***	-0.170	8.208
	(0.086)	(0.100)	(0.090)	(23.250)
Tax per capita	-0.0315***	-0.035***	-0.077***	0.708
	(0.003)	(0.004)	(0.014)	(2.047)
Observations	384	384	288	288
	[5]	[6]	[7]	[8]
Panel B: First-stage results				
STEM	0.003***	0.003***	0.004***	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Density	0.290	0.358	1.481***	0.063
	(0.219)	(0.225)	(0.468)	(0.122)
Air quality index	-0.002	-0.003	0.000	0.000
	(0.002)	(0.002)	(0.004)	(0.001)
Home price index	0.666***	0.786***	0.295	0.361***
	(0.117)	(0.121)	(0.195)	(0.048)
Tax per capita	0.030***	0.035***	0.155***	0.032***
	(0.005)	(0.005)	(0.009)	(0.002)
Cragg-Donald Wald F	38.68	34.69	23.88	0.12
Stock-Yogo critical value at 10%	16.38	—"—	—"—	—"—

Notes: **Panel A** columns [1] to [4] have as dependent variable the logarithm of the number of highly educated individuals entering a state (immigrants). The main control variables are the estimated values of various measures for innovation and productivity, $\widehat{InnProd}$. Specifically, in column [1] the number of patents per 100,000, [2] the aggregated number of patents, [3] labor productivity (multiplied by 10,000), [4] total factor productivity (TFP). **Panel B** columns [5] to [8] have as dependent variables the number of patents per 100,000, the aggregated number of patents, labor productivity, and total factor productivity (TFP), respectively. Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All models include state fixed effects. Significance levels: *** 1%, ** 5%, * 10%.

ONLINE APPENDIX

Not intended for publication

This online appendix accompanies the paper entitled:

"On the Nexus between Innovation, Productivity, and Migration of U.S. University Graduates"

Appendix A: State Rankings

Table A1: Ranking of U.S. states according to patents and the estimated TFP

Ranking	State	Mean TFP	Ranking	State	Mean Patents
1	California	15.657	1	California	87570.75
2	New York	14.744	2	New York	43610.75
3	Texas	14.519	3	Texas	26187.88
4	Florida	13.747	4	Illinois	22913
5	Illinois	13.495	5	New Jersey	19957.88
6	Pennsylvania	13.143	6	Michigan	18560.88
7	Ohio	12.887	7	Massachusetts	18412.25
8	New Jersey	12.780	8	Ohio	15984.63
9	Michigan	12.437	9	Pennsylvania	12952.13
10	Massachusetts	12.327	10	Minnesota	12630.5
11	Georgia	12.297	11	Washington	12529.75
12	North Carolina	12.187	12	Maryland	11854.5
13	Virginia	12.067	13	Connecticut	11580.13
14	Washington	11.687	14	Florida	9512.375
15	Minnesota	11.486	15	Delaware	9273.125
16	Maryland	11.449	16	Virginia	8400.25
17	Indiana	11.393	17	Colorado	7005.75
18	Missouri	11.342	18	Wisconsin	6999.625
19	Wisconsin	11.327	19	North Carolina	6865.75
20	Arizona	11.233	20	Georgia	5693.625
21	Tennessee	11.232	21	Indiana	5361.375
22	Colorado	11.218	22	Missouri	4532.875
23	Connecticut	11.206	23	DC	4456.875
24	Louisiana	10.753	24	Oregon	3972.375
25	Oregon	10.327	25	Nevada	3885.125
26	Alabama	10.315	26	Utah	3338
27	Kentucky	10.207	27	Arizona	3209.875
28	South Carolina	10.195	28	Tennessee	2879.75
29	Oklahoma	10.037	29	Iowa	2554.625
30	Iowa	9.988	30	Idaho	2520.375
31	Nevada	9.643	31	Kansas	1892.875
32	Kansas	9.601	32	South Carolina	1790
33	Utah	9.436	33	New Hampshire	1786.5
34	Arkansas	9.221	34	Kentucky	1695
35	Mississippi	8.956	35	New Mexico	1466.625
36	Nebraska	8.882	36	Oklahoma	1422.125
37	New Mexico	8.557	37	Rhode Island	1216.25
38	Delaware	8.416	38	Alabama	1124.5
39	New Hampshire	8.223	39	Louisiana	995.75
40	West Virginia	8.197	40	Nebraska	832.375
41	Hawaii	8.160	41	Arkansas	531.5

42	Maine	7.794	42	Maine	463.75
43	Idaho	7.772	43	Mississippi	398.75
44	Rhode Island	7.674	44	Vermont	370
45	DC	7.566	45	Montana	314.125
46	Alaska	7.369	46	South Dakota	255.625
47	South Dakota	7.090	47	Wyoming	224.125
48	Montana	6.923	48	West Virginia	214
49	Wyoming	6.773	49	Hawaii	213.875
50	North Dakota	6.555	50	North Dakota	184.5
51	Vermont	6.312	51	Alaska	73.5

Notes: Average values for the years 1993, 1995, 1997, 1999, 2003, 2006, 2008, and 2010

Table A2: Ranking of U.S. states according to the number of high-tech firms

State	# high-tech firms	Ranking	Per 100,000	Ranking
Massachusetts	134.63	4	2.16	1
Connecticut	57.38	11	1.70	2
New Jersey	131.00	5	1.58	3
California	480.50	1	1.42	4
Colorado	56.13	12	1.36	5
Minnesota	57.50	10	1.19	6
Delaware	8.50	31	1.10	7
District of Columbia	5.88	35	1.05	8
New York	179.00	2	0.96	9
Nevada	17.75	26	0.91	10
Utah	20.25	23	0.91	11
New Hampshire	10.63	29	0.88	12
Maryland	45.50	16	0.86	13
Virginia	52.00	13	0.74	14
Texas	147.50	3	0.71	15
Washington	40.88	17	0.69	16
Rhode Island	7.00	33	0.69	17
Pennsylvania	82.13	7	0.67	18
Illinois	81.50	8	0.67	19
Wisconsin	34.25	19	0.64	20
Georgia	50.38	14	0.64	21
Oregon	20.25	24	0.60	22
Arizona	29.63	20	0.59	23
Ohio	61.13	9	0.54	24
Florida	85.13	6	0.54	25
Michigan	49.25	15	0.50	26
Kansas	12.50	27	0.47	27
North Carolina	37.88	18	0.47	28
Missouri	25.50	21	0.46	29
Indiana	23.00	22	0.38	30
Oklahoma	11.63	28	0.34	31
Idaho	4.25	40	0.32	32
Tennessee	17.88	25	0.32	33
Iowa	8.50	32	0.29	34
Nebraska	4.38	39	0.26	35
Alaska	1.63	47	0.25	36
South Dakota	1.88	46	0.24	37
Hawaii	3.00	42	0.24	38
Montana	2.00	45	0.22	39
Louisiana	9.25	30	0.21	40
Maine	2.38	44	0.19	41

Mississippi	4.50	38	0.16	42
Alabama	6.75	34	0.15	43
New Mexico	2.50	43	0.14	44
South Carolina	5.50	36	0.14	45
Kentucky	5.50	37	0.14	46
Arkansas	3.13	41	0.12	47
Wyoming	0.38	49	0.07	48
Vermont	0.38	50	0.06	49
West Virginia	0.88	48	0.05	50
North Dakota	0.00	51	0.00	51

NOTES: This table shows the rankings of U.S. states in terms of the number of high-tech firms (both in absolute numbers and per 100,000 inhabitants). The calculation is based on COMPUSTAT two-digit SIC codes. The industries used are: biotechnology and pharmaceutics, aircraft and space aircraft industry, medical instruments (precision instruments), radio, television, and communication equipment, office accounting and computing machinery, electrical machinery, motor vehicles, railroad and transport equipment, chemical industry, and machinery and equipment. Average values for the years 1993, 1995, 1997, 1999, 2003, 2006, 2008, and 2010

Table A3: Amenity scores, entrepreneurs' educational level, academic R&D expenditures, and taxes per capita.

State	Home price index	Air quality index	Entrepreneur's education	Academic R&D expenditures per capita (in logs)	Taxes per capita
Alabama	1.12	61.88	2.59	-2.22	18.67
Alaska	1.18	30.88	2.84	-1.82	57.96
Arizona	1.20	70.25	2.99	-2.26	23.49
Arkansas	1.14	46.38	2.52	-2.88	20.60
California	1.29	88.31	3.18	-2.05	27.52
Colorado	1.01	42.81	3.15	-1.96	25.76
Connecticut	1.20	42.94	3.26	-1.86	35.61
DC	1.48	52.50	3.68	-0.78	46.03
Delaware	1.34	61.25	2.82	-2.18	26.85
Florida	1.28	42.88	2.90	-2.80	31.73
Georgia	1.04	56.88	2.78	-2.12	23.98
Hawaii	1.55	25.13	3.11	-2.04	31.41
Idaho	1.23	37.56	2.93	-2.76	18.96
Illinois	1.13	66.75	3.05	-2.24	29.49
Indiana	1.07	60.38	2.72	-2.35	21.95
Iowa	1.08	36.63	2.75	-1.90	23.25
Kansas	1.08	33.75	2.88	-2.31	25.00
Kentucky	1.08	56.00	2.59	-2.64	22.89
Louisiana	1.13	50.13	2.79	-2.30	25.02
Maine	1.21	34.19	2.81	-3.04	27.66
Maryland	1.38	39.25	3.17	-1.09	24.23
Massachusetts	1.10	52.38	3.35	-1.34	24.44
Michigan	0.94	59.88	2.80	-2.16	24.04
Minnesota	1.08	39.75	2.92	-2.33	27.25
Mississippi	1.11	41.38	2.55	-2.53	20.77
Missouri	1.09	53.13	2.66	-2.19	21.69
Montana	1.24	68.13	2.94	-2.13	20.15
Nebraska	1.05	44.38	2.81	-1.96	24.98
Nevada	1.24	59.13	2.98	-2.79	33.43
New Hampshire	1.10	37.63	2.92	-1.95	28.21
New Jersey	1.28	43.13	3.22	-2.59	38.98
New Mexico	1.21	50.13	3.02	-1.85	23.02
New York	1.23	34.00	3.24	-1.95	35.25
North Carolina	1.11	52.50	2.84	-1.91	23.98
North Dakota	1.20	30.38	2.82	-1.88	27.41
Ohio	1.03	61.50	2.69	-2.35	23.42
Oklahoma	1.10	43.75	2.76	-2.61	20.04
Oregon	1.22	31.25	3.00	-2.17	17.08

Pennsylvania	1.26	57.25	2.87	-1.96	24.22
Rhode Island	1.29	42.00	3.19	-1.86	28.97
South Carolina	1.11	46.13	2.81	-2.46	21.65
South Dakota	1.15	28.00	2.72	-2.85	26.05
Tennessee	1.10	56.31	2.69	-2.45	25.15
Texas	1.08	63.00	2.87	-2.20	30.52
Utah	1.12	55.13	3.02	-1.98	20.76
Vermont	1.23	34.13	2.97	-1.99	29.82
Virginia	1.27	48.00	3.04	-2.38	26.05
Washington	1.19	42.88	3.05	-2.10	35.78
West Virginia	1.15	43.63	2.53	-2.95	21.22
Wisconsin	1.10	42.25	2.71	-1.99	26.69
Wyoming	1.24	16.13	2.91	-2.25	44.98

Notes: Average values for the years 1993, 1995, 1997, 1999, 2003, 2006, 2008, and 2010.

Table A4: Top five majors for the most innovative and least innovative states for natives.

	Top 5 in patents					Bottom 5 in patents				
Major/State	CA	NY	TX	IL	NJ	WY	WV	HI	ND	AK
Anthropology and archaeology						4				
Biochemistry and biophysics				1						
Chemical engineering					5		2			
Chemistry	5	4	1		2		3		5	
Civil engineering						1		3		2
Clinical psychology	1	1		2			4		2	4
Economics		5								
Electronics/Communications	2		2		3	2				5
Environmental science or studies		2	4	5						3
General psychology					1					
Geological sciences, other								2		
Industry and manufacturing									3	
Mechanical engineering			3	3						1
Nursing						3				
OTHER biological sciences								1		
OTHER psychology		3	5	4			1			
Physics	4						5	5		
Plant sciences						5			1	
Political science								4		
Sociology	3				4				4	

NOTES: This table provides the most frequent majors encountered among the interviewees in SESTAT for the five most innovative and five less innovative states across USA for people born in the state of study. The ranking starts from one and ends in five in descending order; that is with [1] we have the most frequent major, while with [5] the least frequent.

Table A5: Top five majors for the five most innovative and five less innovative states for graduate migrants.

	Top 5 in patents					Bottom 5 in patents				
Major/State	CA	NY	TX	IL	NJ	WY	WV	HI	ND	AK
Anthropology and archaeology						5		1		
Biochemistry and Biophysics	4			4	5					
Chemical engineering			2		4		2			
Chemistry	2	1	1	1	1		1		3	
Civil engineering						3				3
Clinical psychology							3	3		
Economics		3		3						
Electronics/Communications	3		4		3					5
Environmental sciences										2
General psychology						1				
Geological sciences						2				1
Mechanical engineering			5							4
Nursing						4				
Other agricultural sciences									2	
Other biological sciences	5	5						4		
Physics	1	2	3	2	2		4	5		
Plant sciences									1	
Political science		4								
Sociology				5			5	2	4	
Zoology, general									5	

NOTES: This table provides the most frequent majors for SESTAT interviewees for the five most innovative and least innovative states for people migrating to there. The ranking starts from one and ends in five in descending order; that is with [1] we have the most frequent major, while with [5] the least frequent.

Appendix B: Auxiliary Models

Table B1: Instrumental variables approach with *Top1* as instrument

	[1]	[2]	[3]	[4]
Panel A: Main results				
$\widehat{InnProd}$	0.056	0.056	0.124	1.908
	(0.053)	(0.053)	(0.075)	(1.554)
Density	-0.055	-0.060	-0.285	-0.260
	(0.080)	(0.080)	(0.146)	(0.293)
Air quality index	-0.001	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.003)
Home price index	-0.114*	-0.122*	-0.0813	-0.723
	(0.057)	(0.061)	(0.058)	(0.572)
Tax per capita	-0.021***	-0.021***	-0.037**	-0.079
	(0.002)	(0.002)	(0.011)	(0.050)
Observations	384	384	288	288
	[5]	[6]	[7]	[8]
Panel B: First-stage results				
Top1	5.765***	5.692***	4.697***	0.124*
	(0.790)	(0.812)	(1.336)	(0.075)
Density	-0.019	0.057	0.986**	0.081
	(0.209)	(0.215)	(0.470)	(0.116)
Air quality index	-0.002	-0.002	0.002	0.000
	(0.002)	(0.002)	(0.004)	(0.001)
Home price index	0.450***	0.572***	0.123	0.344***
	(0.119)	(0.122)	(0.208)	(0.049)
Tax per capita	0.009*	0.015***	0.135***	0.031***
	(0.005)	(0.005)	(0.009)	(0.002)
Cragg-Donald Wald F	53.20	49.13	12.37	2.163
Stock-Yogo critical value at 10%	16.38	—"—	—"—	—"—

Notes: **Panel A** columns [1] to [4] have as dependent variable the logarithm of the number of highly educated individuals entering a state (immigrants). The main control variables are the estimated values of various measures for innovation and productivity, $\widehat{InnProd}$. Specifically, in column [1] the number of patents per 100,000, [2] the aggregated number of patents, [3] labor productivity (multiplied by 10,000), [4] total factor productivity (TFP). **Panel B** columns [5] to [8] have as dependent variables the number of patents per 100,000, the aggregated number of patents, labor productivity, and total factor productivity (TFP), respectively. Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All models include state fixed effects. Significance levels: *** 1%, ** 5%, * 10%.

Table B2 : Instrumental variables approach with *Firms20* as instrument

	[1]	[2]	[3]	[4]
Panel A: Main results				
$\widehat{InnProd}$	0.835	0.381**	0.430	0.561***
	(0.537)	(0.135)	(0.349)	(0.147)
Density	-0.093	-0.132	-0.601	-0.162
	(0.205)	(0.113)	(0.417)	(0.152)
Air quality index	0.0001	-0.001	-0.002	-0.002
	(0.002)	(0.001)	(0.002)	(0.002)
Home price index	-0.632	-0.366**	-0.180	-0.236**
	(0.376)	(0.120)	(0.144)	(0.081)
Tax per capita	-0.038**	-0.030***	-0.081	-0.036***
	(0.013)	(0.004)	(0.051)	(0.006)
Observations	336	336	288	288
	[5]	[6]	[7]	[8]
Panel B: First-stage results				
Firms20	0.524	1.148***	0.722	1.657***
	(0.370)	(0.372)	(0.572)	(0.158)
Density	-0.045	0.004	0.945*	0.012
	(0.270)	(0.271)	(0.485)	(0.098)
Air quality index	-0.002	-0.002	0.003	0.771
	(0.003)	(0.003)	(0.004)	(0.972)
Home price index	0.592***	0.602***	0.198	0.156***
	(0.147)	(0.148)	(0.226)	(0.044)
Tax per capita	0.021***	0.026***	0.145***	0.032***
	(0.006)	(0.006)	(0.009)	(0.002)
Cragg-Donald Wald F	2.007	9.550	1.593	109.5
Stock-Yogo critical value at 10%	16.38	—"—	—"—	—"—

Notes: **Panel A** columns [1] to [4] have as dependent variable the logarithm of the number of highly educated individuals entering a state (immigrants). The main control variables are the estimated values of various measures for innovation and productivity, $\widehat{InnProd}$. Specifically, in column [1] the number of patents per 100,000, [2] the aggregated number of patents, [3] labor productivity (multiplied by 10,000), [4] total factor productivity (TFP). **Panel B** columns [5] to [8] have as dependent variables the number of patents per 100,000, the aggregated number of patents, labor productivity, and total factor productivity (TFP), respectively. Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All models include state fixed effects. Significance levels: *** 1%, ** 5%, * 10%.

Table B3 : Instrumental variables approach with *STEM(x)Firms20* as instrument

	[1]	[2]	[3]	[4]
Panel A: Main results				
$\widehat{InnProd}$	0.485***	0.495***	0.396***	-44.27
	(0.085)	(0.090)	(0.091)	(253.3)
Density	-0.097	-0.141	-0.566**	3.100
	(0.128)	(0.133)	(0.220)	(19.2)
Air quality index	-0.001	-0.000	-0.002	0.0197
	(0.001)	(0.001)	(0.002)	(0.132)
Home price index	-0.396***	-0.455***	-0.169	15.97
	(0.0860)	(0.0970)	(0.089)	(91.62)
Tax per capita	-0.030***	-0.033***	-0.076***	1.392
	(0.003)	(0.004)	(0.014)	(8.069)
Observations	336	336	288	288
	[5]	[6]	[7]	[8]
Panel B: First-stage results				
STEM(x)Firms20	2.64e-04 ***	2.58e-04***	0.495***	-3.05e-06
	(4.44e-05)	(4.54e-05)	(0.090)	(1.77e-0.5)
Density	0.325	0.409	1.435***	0.068
	(0.261)	(0.267)	0.468	(0.122)
Air quality index	-0.004	-0.004	0.001	0.000
	(0.002)	(0.003)	(0.004)	(0.001)
Home price index	0.665***	0.772***	0.287	0.362***
	(0.128)	(0.131)	(0.196)	(0.048)
Tax per capita	0.029***	0.035***	0.154***	0.032***
	(0.006)	(0.006)	(0.009)	(0.002)
Cragg-Donald Wald F	34.94	32.19	22.38	0.0298
Stock-Yogo critical value at 10%	16.38	—"—	—"—	—"—

Notes: **Panel A** columns [1] to [4] have as dependent variable the logarithm of the number of highly educated individuals entering a state (immigrants). The main control variables are the estimated values of various measures for innovation and productivity, $\widehat{InnProd}$. Specifically, in column [1] the number of patents per 100,000, [2] the aggregated number of patents, [3] labor productivity (multiplied by 10,000), [4] total factor productivity (TFP). **Panel B** columns [5] to [8] have as dependent variables the number of patents per 100,000, the aggregated number of patents, labor productivity, and total factor productivity (TFP), respectively. Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All models include state fixed effects. Significance levels: *** 1%, ** 5%, * 10%.

Table B4 : Instrumental variables approach with *STEM(x)Top1* as instrument

	[1]	[2]	[3]	[4]
Panel A: Main results				
$\widehat{InnProd}$	0.141**	0.150**	0.189**	-2.403
	(0.052)	(0.055)	(0.071)	(1.579)
Density	-0.0536	-0.065	-0.352*	0.054
	(0.078)	(0.078)	(0.153)	(0.320)
Air quality index	-0.001	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.003)
Home price index	-0.172**	-0.196**	-0.102	0.835
	(0.055)	(0.061)	(0.061)	(0.584)
Tax per capita	-0.023***	-0.024***	-0.046***	0.059
	(0.002)	(0.002)	(0.011)	(0.051)
Observations	384	384	288	288
	[5]	[6]	[7]	[8]
Panel B: First-stage results				
STEM(x)Top1	19.401***	18.195***	18.033***	-1.790
	(2.696)	(2.788)	(4.470)	(1.120)
Density	-0.046	0.032	0.942**	0.062
	(0. 209)	(0.217)	(0.467)	(0.119)
Air quality index	-0.001	-0.002	0.002	0.001
	(0.002)	(0.002)	(0.004)	(0.001)
Home price index	0.486***	0.617***	0.126	0.378***
	(0.118)	(0.122)	(0.204)	(0.049)
Tax per capita	0.016***	0.022***	0.141***	0.032***
	(0.005)	(0.005)	(0.009)	(0.002)
Cragg-Donald Wald F	51.80	42.58	16.27	2.557
Stock-Yogo critical value at 10%	16.38	—"—	—"—	—"—

Notes: **Panel A** columns [1] to [4] have as dependent variable the logarithm of the number of highly educated individuals entering a state (immigrants). The main control variables are the estimated values of various measures for innovation and productivity, $\widehat{InnProd}$. Specifically, in column [1] the number of patents per 100,000, [2] the aggregated number of patents, [3] labor productivity (multiplied by 10,000), [4] total factor productivity (TFP). **Panel B** columns [5] to [8] have as dependent variables the number of patents per 100,000, the aggregated number of patents, labor productivity, and total factor productivity (TFP), respectively. Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All models include state fixed effects. Significance levels: *** 1%, ** 5%, * 10%.

Table B5: Three Stage Least Squares Estimation – weighted results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equation 1: the dependent variable is highly-skilled migration to the state								
InnProd	0.685***	0.371***	0.248***	0.239**	0.725***	0.516***	0.364***	0.588***
	(0.097)	(0.046)	(0.065)	(0.112)	(0.107)	(0.046)	(0.063)	(0.075)
Density	0.140***	0.155***	0.216***	0.170	0.032	0.007	-0.111	-0.089
	(0.063)	(0.046)	(0.079)	(0.117)	(0.072)	(0.046)	(0.085)	(0.078)
Gini	-0.876	-1.443***	0.536	1.566	-0.720	-0.236	-0.683	-3.304***
	(0.969)	(0.486)	(1.228)	(1.863)	(1.135)	(0.376)	(1.226)	(1.249)
Air quality index	0.017***	0.013***	0.025***	0.016*	0.015***	0.002	0.021***	-0.016**
	(0.002)	(0.002)	(0.003)	(0.008)	(0.004)	(0.003)	(0.003)	(0.007)
Home-price index	-0.391***	-0.264***	-0.291*	-0.137	0.025	-0.007	0.043	0.025
	(0.105)	(0.058)	(0.152)	(0.147)	(0.116)	(0.040)	(0.148)	(0.121)
Tax per capita	-0.001	0.006	-0.005	0.017	0.016*	0.001	0.024**	-0.024**
	(0.007)	(0.004)	(0.011)	(0.011)	(0.009)	(0.005)	(0.012)	(0.010)
Constant	2.975***	2.963***	2.403***	0.896	1.581**	1.235***	1.001	2.351***
	(0.634)	(0.324)	(0.731)	(0.663)	(0.744)	(0.292)	(0.789)	(0.579)
Equation 2: the dependent variables are the different proxies for innovation or productivity								
Controls\Dependent variables	Ln(patents) per 100,000	Ln(patents)	Labor productivity	TFP	Ln(patents) per 100,000	Ln(patents)	Labor productivity	TFP
Ln (HK graduates)	0.399***	1.238***	0.008	2.040***	0.489***	1.773***	0.367	2.806***
	(0.075)	(0.085)	(0.152)	(0.162)	(0.156)	(0.165)	(0.242)	(0.184)
STEM (x) Top1	21.186***	34.150***	57.619***	24.584***	16.045***	5.231	36.231***	-1.653
	(3.471)	(3.949)	(7.097)	(7.803)	(5.847)	(5.829)	(9.227)	(7.332)
Density	0.251***	0.183***	0.933***	0.053	0.109	0.029	0.663***	0.064
	(0.048)	(0.054)	(0.092)	(0.084)	(0.072)	(0.074)	(0.114)	(0.087)
Ln (R&D capita)	0.382***	0.329***	1.456***	0.082	0.469***	0.058	1.188***	-0.880***
	(0.056)	(0.051)	(0.130)	(0.110)	(0.140)	(0.127)	(0.230)	(0.165)
Entrepreneur average education					0.574**	0.105	1.788***	-0.818**
					(0.235)	(0.217)	(0.427)	(0.357)
Constant	1.939***	0.610	9.361***	-0.989	0.282	-1.812***	2.618**	-3.620***
	(0.388)	(0.438)	(0.800)	(0.826)	(0.658)	(0.575)	(1.140)	(0.929)
N	384	384	288	288	192	192	192	192
χ^2 for equation 1	351.67	966.37	221.42	269.71	253.78	730.66	234.79	327.75
R^2 for equation 1	0.414	0.734	0.409	0.721	0.380	0.791	0.348	0.720
χ^2 for equation 2	373.33	1017.44	561.22	708.18	0.489	605.25	353.02	799.84
R^2 for equation 2	0.497	0.780	0.659	0.813	0.489	0.790	0.635	0.871

NOTES: The variable representing density is computed based on regions consisting about 75% of the states' whole population (starting from the most populous region to the least populous). Columns (1) to (8) have the following proxies for innovation or productivity (InnProd): columns (1) and (5) the natural logarithm of patents per 100,000; columns (2) and (6) the raw natural logarithm of patents; columns (3) and (7) the labor productivity per hour; columns (4) and (8) the total factor productivity (TFP). Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All regressions have been tested for identification through the order and rank condition and pass the test. Significance levels: *** 1%, ** 5%, * 10%.

Table B6: Two Stage Least Squares Estimation – weighted results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equation 1: the dependent variable is highly-skilled migration to the state								
InnProd	0.731***	0.672***	0.301***	0.833***	0.725***	0.572***	0.389***	0.649***
	(0.112)	(0.059)	(0.067)	(0.125)	(0.113)	(0.051)	(0.065)	(0.078)
Density	0.174***	0.003	0.216***	-0.261**	0.171**	0.076	0.061	-0.109
	(0.067)	(0.052)	(0.081)	(0.126)	(0.078)	(0.050)	(0.089)	(0.080)
Gini	4.324***	-0.485	2.671**	-9.895***	3.956***	0.055	2.827*	-6.388***
	(1.173)	(0.759)	(1.274)	(2.273)	(1.489)	(0.826)	(1.476)	(1.372)
Air quality index	0.014***	-0.004	0.023***	-0.032***	0.018***	0.001	0.024***	-0.021***
	(0.003)	(0.003)	(0.003)	(0.009)	(0.004)	(0.003)	(0.004)	(0.007)
Home-price index	-0.409***	-0.218**	-0.283*	0.150	-0.088	-0.002	-0.042	0.169
	(0.138)	(0.091)	(0.159)	(0.178)	(0.183)	(0.106)	-0.186	(0.138)
Tax per capita	-0.031***	-0.042***	-0.028**	-0.051***	-0.015	-0.025***	-0.020	-0.035***
	(0.009)	(0.006)	(0.012)	(0.013)	(0.012)	(0.008)	(0.013)	(0.011)
Constant	0.665	1.978***	1.401*	4.935***	-0.391	1.358***	-0.180	3.892***
	(0.703)	(0.394)	(0.750)	(0.813)	(0.882)	(0.469)	(0.898)	(0.641)
Equation 2: the dependent variables are the different proxies for innovation or productivity								
Controls\Dependent variables	Ln(patents) per 100,000	Ln(patents)	Labor productivity	TFP	Ln(patents) per 100,000	Ln(patents)	Labor productivity	TFP
Ln (HK graduates)	0.429***	1.281***	0.022	2.040***	0.548***	1.787***	0.422*	2.786***
	(0.076)	(0.086)	(0.153)	(0.163)	(0.162)	(0.171)	(0.249)	(0.187)
STEM (x) Top1	12.646***	26.353***	52.559***	24.574***	12.693*	10.237	31.163***	0.167
	(3.783)	(4.330)	(7.234)	(7.901)	(6.635)	(7.005)	(10.211)	(7.678)
Density	0.229***	0.148***	0.923***	0.053	0.128*	0.087	0.666***	0.072
	(0.048)	(0.055)	(0.092)	(0.085)	(0.077)	(0.081)	(0.119)	(0.089)
Ln (R&D capita)	0.594***	0.588***	1.564***	0.083	0.585***	0.060	1.249***	-1.059***
	(0.067)	(0.077)	(0.133)	(0.132)	(0.157)	(0.166)	(0.242)	(0.182)
Entrepreneur average education					0.267	-0.323	1.646***	-0.691*
					(0.327)	(0.345)	(0.503)	(0.378)
Constant	2.597***	1.269***	9.728***	-0.987	1.182	-0.905	3.042**	-4.295***
	(0.406)	(0.465)	(0.810)	(0.850)	(0.870)	(0.918)	(1.339)	(1.007)
N	384	384	288	288	192	192	192	192
R^2 for equation 1	0.435	0.751	0.400	0.208	0.436	0.799	0.406	0.642
R^2 for equation 2	0.512	0.788	0.661	0.813	0.482	0.792	0.630	0.873

NOTES: The variable representing density is computed based on regions consisting about 75% of the states' whole population (starting from the most populous region to the least populous). Columns (1) to (8) have the following proxies for innovation or productivity (InnProd): columns (1) and (5) the natural logarithm of patents per 100,000; columns (2) and (6) the raw natural logarithm of patents; columns (3) and (7) the labor productivity per hour; columns (4) and (8) the total factor productivity (TFP). Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All regressions have been tested for identification through the order and rank condition and pass the test. Significance levels: *** 1%, ** 5%, * 10%.

Table B7: Instrumental variables approach with *STEM* as instrument - weighted

	[1]	[2]	[3]	[4]
Panel A: Main results				
$\widehat{InnProd}$	0.428***	0.435***	0.469***	-7.871
	(0.0470)	(0.0497)	(0.0988)	(6.292)
Density	-0.019	-0.052	-0.653**	1.900
	(0.083)	(0.086)	(0.238)	(1.830)
Air quality index	-0.000	-0.000	0.001	0.007
	(0.001)	(0.001)	(0.002)	(0.010)
Home price index	-0.159***	-0.179***	-0.137	2.291
	(0.044)	(0.047)	(0.081)	(1.830)
Tax per capita	-0.035***	-0.0391***	-0.083***	0.193
	(0.002)	(0.003)	(0.014)	(0.169)
Observations	384	384	288	288
	[5]	[6]	[7]	[8]
Panel B: First-stage results				
STEM	0.003***	0.003***	0.002***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Density	0.162	0.234	1.370***	0.240**
	(0.180)	(0.185)	(0.431)	(0.107)
Air quality index	-0.004**	-0.004*	-0.003	0.001
	(0.002)	(0.002)	(0.004)	(0.001)
Home price index	0.472***	0.511***	0.352**	0.286***
	(0.082)	(0.085)	(0.148)	(0.034)
Tax per capita	0.041***	0.050***	0.145***	0.026***
	(0.004)	(0.004)	(0.008)	(0.002)
Cragg-Donald Wald F	98.10	89.68	25.26	1.503
Stock-Yogo critical value at 10%	16.38	—"—	—"—	—"—

Notes: **Panel A** columns [1] to [4] have as dependent variable the logarithm of the number of highly educated individuals entering a state (immigrants). The main control variables are the estimated values of various measures for innovation and productivity, $\widehat{InnProd}$. Specifically, in column [1] the number of patents per 100,000, [2] the aggregated number of patents, [3] labor productivity (multiplied by 10,000), [4] total factor productivity (TFP). **Panel B** columns [5] to [8] have as dependent variables the number of patents per 100,000, the aggregated number of patents, labor productivity, and total factor productivity (TFP), respectively. Data from Alaska, the District of Columbia, and Hawaii are absent from these specifications. All models include state fixed effects. Significance levels: *** 1%, ** 5%, * 10%.