By how much does inter-regional immigration boost innovation?

Research in Applied Economics

Department of Economics at the University of Warwick

Course of Studies:	Bachelor of Science in Economics
Student ID:	1412036
Word Count:	4832 words, including 271 in tables
Date:	April 24, 2017

Acknowledgements

This paper wouldn't have been possible without the support and assistance provided by Professors Wiji Arulampalam and Gianna Boero, who as supervisor and personal tutor respectively, helped me from pinning down my research question within the economics of innovation to the last results presentation. Their insight on how to use panel data techniques and interpret its results has been key to this project. Thank you for your time and effort.

Abstract

This paper measures the extent to which internal migration between US states boost innovation as measured by patents per capita. Similar studies of the relationship between immigration and innovation have found that a one percentage point rise in the share of immigrant college graduates in the population increases patents per capita by 6%, as implied by the 2003 National Survey of College Graduates, or is associated with a 12-15% increase in patenting per capita (Hunt and Gauthier-Loiselle, 2009). Using a 2005-2011 panel of data at the US state level, I don't find any evidence of a positive impact of receiving immigrants from other US states on patenting per capita. I isolate the causal effect, which turns out to be insignificantly different from zero, by instrumenting the value of present inter-state net migration in a state with previous 1-period and 2-period values of inter-state net migration in the same state.

Contents

1 Introduction

Economists have extensively studied the impact of labour mobility on wages, inequality, tax revenue, government expenditure and skills composition on the host country. For example, in an influential paper Card (2012) argues that the negative effect of immigration on real wages and employment outcomes of native workers in the United States and the United Kingdom has been relatively small compared to the effect of technological change. By contrast, the effect of labour mobility on innovation and technical progress has attracted less research. Immigrants could directly increase innovation in the host state through their participation in research. Alternatively, immigration could increase innovation by providing complementary skills in research or management and entrepreneurship or bringing new skills altogether.

The existing literature that relates immigration and innovation has focused on the effects of international labour mobility, in particular skilled immigrants such as engineers and scientists, on knowledge production as measured by patents or scientific articles. I will focus on another form of migration: internal mobility between regions of the same country. This presents some advantages: it limits the potential endogeneity caused by different migration policies at different points in time (since domestic workers in developed countries are typically not subject to migration restrictions). It also allows us to look at immigrants in posession of a wide range of skills and more broadly how all categories of workers enter the knowledge production function.

This paper aims to assess the effect of interstate labour mobility between US states in the amount of innovation that takes place in each state as measured by patents per capita. In other words, does a surge in the net immigration coming from other US states into a particular state cause an increase in innovation? The purpose of studying patents per capita is that it is a proxy for innovation, which itself is a driver of productivity growth. If immigrants increase patents per capita then increasing immigration can be thought of as a productivity enhancing policy. This is especially relevant in the current environment of poor productivity growth. Furthermore, this analysis could shed some light on a relatively unstudied economic effect of immigration, adding to the debate in developed countries over what immigrant's net contribution to the economy and society is.

I find no evidence of a causal relationship between net inter-regional immigration and innovation. The use of both the within estimator and IV estimation yield insignificant coefficients for the immigration variable in my econometric model. This results are robust to several changes in the sample and model specification. This result, which is in marked contrast with the recent literature on the topic, might be caused by the fact I am not considering the educational and professional status of the immigrants. Furthermore, inter-state mobility could have an effect on innovation in the long run. This possibility is not covered in this paper due to lack of data on inter-regional migration between U.S. states prior to 2005.

2 Literature Review

It is widely acknowledged that the economic literature that aims to explain innovation as the product of a series of inputs, such as human and physical capital, goes back to the model of endogenous technological change developed by Romer (1990). A crucial feature of this model is that the knowledge production function is linear in the existing knowledge stock and in human capital employed in the RD sector.

In order to obtain an objective measure of innovation I will resort to patent applications per capita, which Peri and Botazzi (2004) shows to be highly correlated with total factor productivity at the country level. However, as Grilliches (1990) points out, there remain concerns abouth how well patents can measure the quality of innovations or that the total numbers might be affected by the shifts in the industry. I resort to Furman, Porter and Stern (2002), Ulku (2004) and Jung et al. (2008), who empirically estimate the effect of R&D spending and GDP per capita on the patent stock, as well as Falk (2007) to determine which factors enter the patent production function.

In a similar approach to the one I will use, several authors aim directly to assess the impact of immigration on innovation. Peri (2007) uses a panel of data at the US state level to measure the importance of the immigrants' skills in producing new ideas. He extracts US Census microdata and data from the NBER database for immigration and patents respectively. Peri is interested in measuring the impact of the number of foreign born PhD graduates in STEM subjects working in a state on innovation, controling for decade and state fixed effects. However, serious concerns about the endogeneity of the immigration flow variable remain, since it is possible that immigrants are attracted to states that have a higher innovation or growth rate.

Peri's analysis is extended by Hunt and Gauthier-Loiselle (2009), who aim to correct for the endogeneity of the immigration variable. They combine individual and panel data (extracted from the US. Patent and Trademark Office) on US patents at the State level. Their main contribution is the use of the national (US) change in the number of skilled immigrants from a region of origin (such as Europe, Asia, Africa, etc.) weighted by the state's share of the 1940 total of immigrants who originated from that region as an instrument for their immigration variable. Using this technique they find evidence that the 1.3 percentage point increase in the share of the population composed of immigrant college graduates and the 0.7 percentage point increase in the share of post-college immigrants both increased patenting per capita by about 21 percentage points in the US in the period 1990-2000

My analysis will be somewhat similar to Hunt and Gauthier-Loiselle in the sense that I supplement an analysis panel data collected at the state level with IV estimation. The main difference bewtween our papers is the way they define their immigration variable, which is linked to the fact that I am posing a slightly different research question. They define their immigration variable as the share of the population of the state that is comprised of skilled immigrants from outside the US. I define it as the difference between the number of people who arrive in a given US state minus the number of people who leave for another US state in a given year. Mine is a flow variable while theirs is a stock variable. I have opted for this approach is because my research question is related to the labour input in the knowledge production function and how immigration enters this function (while Hunt and Loiselle focus on the human capital input). Because I want to measure by how much innovation increases when there is an increase in the Labour input, due to higher inter-regional immigration, I have chosen this dataset. Secondly, my number of years is only 7 due to lack of data on state patents prior to 2005 in the OECD Database. Thirdly there are significant variations in the methodology. In particular I instrument immigration in a different way. They construct a variable for the predicted change in the number of skilled immigrants from outside the US in each state. I use past 1-period and 2-period lags of the immigration variable itself.

In summary, I go beyond Peri (2007) in establishing a causal relationship between positive net migration flows and the amount of innovation that takes place in US states. The reason for this is that Peri's use of fixed effects does not rule out endogeneity concerns of the immigration variable. Therefore his results can only be interpreted as evidence of a positive association between highly skilled immigration and innovation. Furthermore, my analysis will be more general than Hunt and Gauthier-Loiselle (2009) due to the fact that I am not excluding unskilled immigrants (or any specific type of immigrants, including non active immigrants) from my analysis. Also, it differs from Borjas and Doran (2012) since I will be estimating the net effect of immigrants on the knowledge production in a state in general and not on the knowledge production of state locals, this is, not considering the immigrants, in that state. In that sense I will not be considering the individual forces that might drive changes in innovation but rather the overall short and long run effect.

3 Empirical methodology

My analysis uses a panel of U.S. states with annual data from 2005-2011. I estimate:

$$\log \frac{P_{i,t}}{Pop_{i,t}} = \gamma_0 + \gamma_1 N_{i,t} + \gamma_2 X_{i,t} + \sum_{t=2005}^{2011} c_t + u_{i,t} \tag{1}$$

using the within estimator, where i indexes states, P is the number of patent applications, Pop is state population, N is the net interstate migration as a percentage of the state total population, X is a vector of contemporaneous state controls and c_{t} are a series of time dummies. I am interested in the coefficient γ_1 which I expect to be positive and significant. The covariates in X comprise gross research and development expenditures as a percentage of the state GDP, the logarithm of GDP per capita, the percentage of the labour force who has attained elementary, secondary and tertiary education and the number of permanent residence cards (also known as green cards) a state issues, normalised by the state population, which acts as a proxy for international immigration. Using fixed effects via the within estimator addreses the presence of time invariant state-level heterogeneity. I cluster standard errors by state to allow for serial correlation.

Equation 1 presents an endogeneity problem. In particular, as Hunt and Gauthier-Loiselle (2009) point out, workers are more likely to migrate to states that are innovating. Especially since my analysis is limited to the short run relationship between net inter-state migration and innovation, there might also be unobserved factors, such macroeconomic shocks on output and employment, that vary over time and that affect both net interstate migration and the number of patent applications in a given year. In that case our estimate would be upward biased in a least squares regression.

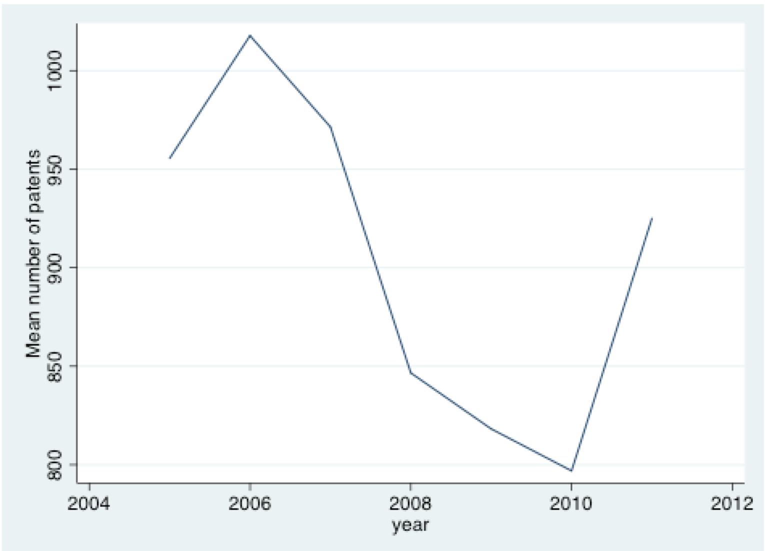
In this paper I devise an instrument to address this issue. After the number of permanent residence cards issued by each state fails to be relevant enough in the first stage, I resort to using the 1-period and 2-period lags of the net immigration variable as instruments for present net immigration variable. The intuition is that the unobserved time-variant heterogeneity that I am worried about likely comes from macroeconomic shocks, such as a recession that affects both the number of patents applications and the number of people moving into the state from another US state. Due to the unforeseen nature of these shocks it is likely that previous immigrants made the decision to move states independently of them. This line of reasoning is analogous to Card (2001) : "While the decisions of previous immigrants were likely based upon previous demand shocks to wages, it is unlikely that those decisions are correlated with current demand shocks."

If previous net immigration values are not correlated with present values of the error term and there is no serial correlation present in our model then our IV estimator will be consistent. Finally I have chosen to use two instruments instead of only using the 1-period lag so that I can test my model for overidentifying restrictions, trading off losing an extra 51 observations.

4 Data and descriptive statistics

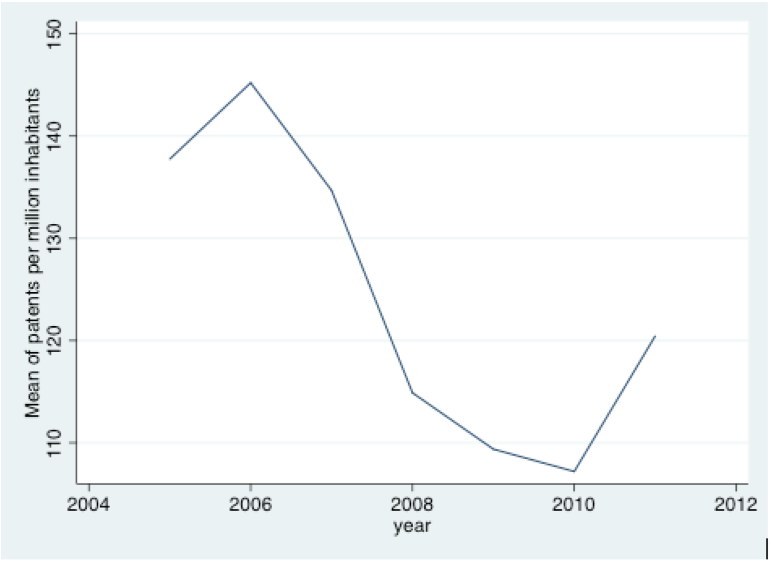
The data on patents at the state level come from the OECD regional statistics database. The sample is comprised of the 51 U.S. States, which include Alaska and Hawaii, as well as the District of Columbia. Data are complete for all variables for all states in every year. My outcome variable is defined as PCT (Patent Cooperaton Treaty) applicatons per million inhabitants. Note that I am using patent applications instead of granted patents as the lag between the applicaton and grant can be of up to 6-10 months. Therefore the literature tends to consider patent applications as more relevant for an investigation of firm and individual behavior than patent grants (Hall, 2005). Patent applications are attributed to a state based on the home address of the inventor. Figures 1 and 2 show the evolution of total patent applications and patent applications per capita from 2005-2011. It would be preferrable to cover a wider period of time in this analysis, unfortunately the available data on net interregional migration is restricted to these seven years. On average the evolution of patenting in U.S. states has been negative for the period, both in absolute and per capita terms While the U.S. state average of patents per million inhabitants was 137.75 in 2005, it fell down to 120.43 in 2011. However the minimum level of patenting was actually reached in 2010 with a statistic of 107.19. Some authors attribute the fall to a series of short term or structural causes such as the effect of business cycles (Park and Hingley, 2017), the 2008 financial crisis, or an increase in patent litigation (Bessen and Meurer, 2012).

Figure 1: Evolution of the mean of patent applications per state.



The data on inter-regional net migration also comes from the OECD regional statistics database, and it has been collected by the Directorate of Public Governance and Territorial Development through an annual ques-

Figure 2: Evolution of the mean of patent applications per capita.

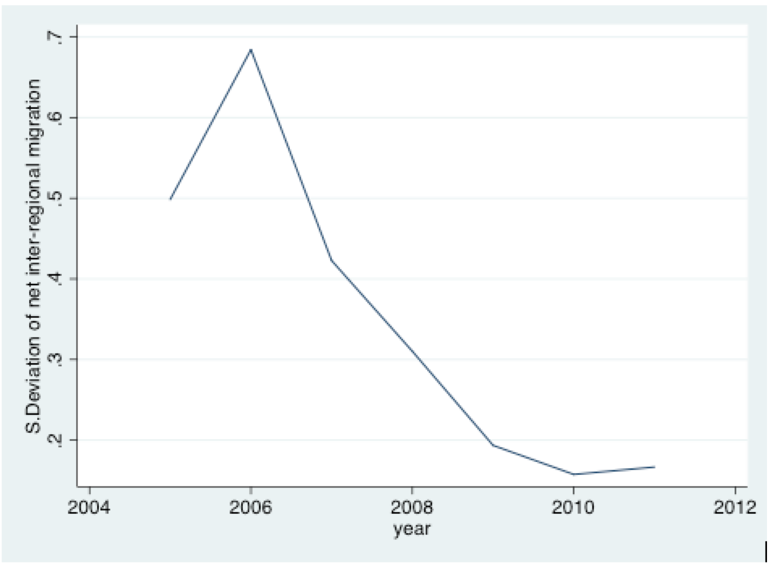


tionnaire sent to the delegates of the Working Party on Territorial Indicators (WPTI). My variable of interest is measured as the percentage migrants moving into the state from other US states minus the percentage of migrants moving from the state to other US states, divided by total population. The OECD defines a migrant as someone born out of state.

Data for the control variables also comes from the OECD regional statistics database, except for the number of people living in each state who have been granted lawful permanent residence in the United States (they are also known as green card recipients). This has been extracted from the Yearbook of Immigration Statistics, Deparment of Homeland security in its 2011 edition. I will be using this as a proxy for the number of immigrants arriving to each state from outside the US due to the current unavailability of those figures. GDP per capita is measured in constant US dollars at purchasing power parity. R&D expenditure is measured in nominal terms as a percentage of nominal GDP. The educaton level of the labour force (elementary, secondary, tertary) is measured as the percentage of the labour force that has achieved that educational attainment.

The variable means and standard deviations, non weighted by the state population, for the full 2005-2011 sample are reported in Table 1. As shown in Figure 3, the standard deviation of interregional net-immigration has decreased in the period from approximately 0.5 to 0.17. At the same time, the number of states whose net immigration figures are higher than 0.5% in absolute value (this is, they either send or receive more than 0.5% of the population to or from other states) has dropped from 9 in 2005 to 0 in 2011. This downwards trend in internal mobility in the US has been also studied by Kaplan and Wohl (2015), and they attribute it to a variety of factors which include falling regional economic specialisation and that more efficient information (as a result of information technology and falling travel costs) has made locations less of an experience good, thereby reducing the need for young people to experiment with living in different places.

Figure 3: Evolution of the standard deviation of net migration.



Finally in Figures 4 and 5 I plot the relationship between the previous 1 year and 2 year values and the current values of inter-regional net migration in each state, respectively. In other words, Figures 4 and 5 are a graphical representation of the first-stage of my IV model. The figures clearly show that states that had a higher value of net migration in the past tend to have higher net immigration in the present.

Figure 4: Relationship between present and previous year net migration.

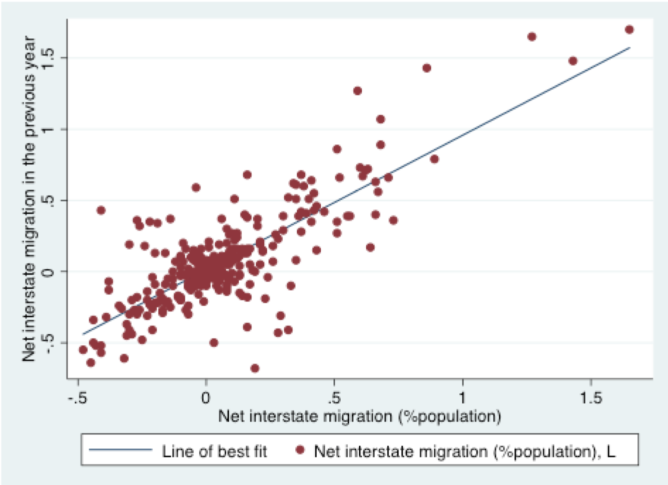
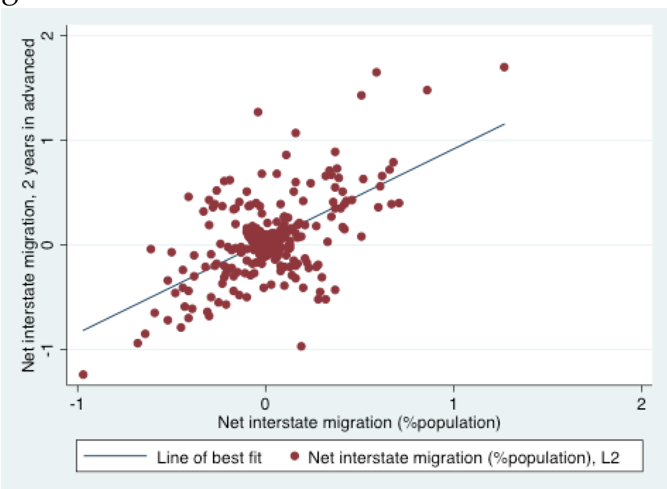


Figure 5: Relationship between present and 2 years in advanced net migration.



5 Results

In Table 2, I estimate the state determinants of log patenting per capita using the within estimator. The regression in column 1 follows the basic specification of equation (1), while the regression in column 2 adds dummy variables each representing a year from 2005-2011. Time dummies are preferred to a linear time trend because they allow the time effect to vary depending on the year in a non-linear fashion. In additon the regression in column 3 lags all the covariates by 1 year to account for the fact that patent applications take on average about six months to process. The coefficients on the value of inter-state net immigration are positive but not significant in any specification. In fact, the only coeffcients that are significant in the base specification are the ones on the percentage of the labour force with elementary, secondary and tertiary education attainment and the log of GDP per capita. The estimates are similar for the 3 types of educational attainments: a 1 point increase in the percentage of the labour force that is in possession of elementary, secondary or tertiary education is associated with a 3% increase in patent applications per million inhabitants. The coefficient on log GDP per capita (measured in thousands of dollars) shows that the elasticity of patents with respect to income per capita is close to 1.

However, when year dummies are added to the model only the coefficient on the tertiary education variable remains significant at the 10% level. The year dummies follow very closely the evolution of patenting outlined in Figure 4. This is indicative of the presence of unobserved factors that affect patenting and that haven't been captured by our model. Furthermore, in the specification with lagged covariates all of the coefficients on the control variables become insignificant.

Table 2: Effect of net inter-regional migration on log patents per capita

	(1) Base specification	(2) Time dummies	(3) Lagged Covariates
Net Inter-regional migration	0.015	0.01	0.04
Number of permanent residence cards awarded/po	-0.07	-0.04	0.0804
% of workforce with tertiary education	2.9**	2.23*	-1.04
% of workforce with secondary education	2.93**	2.28	-1.03
% of workforce with elementary education	3.02**	2.25	-1.07
Gross R&D investment/GDP, x100	-0.03	-0.01	0
Log of GDP per capita	1.03**	0.63	-0.28
Year Dummies (2011 baseline)			
2005		0.23***	
2006		0.29***	0.26***
2007		0.19***	0.19***
2008		0.02	0.03
2009		-0.03	-0.06*
2010		-0.06*	-0.1***
Constant	-299.7**	-229.4	110.8
Observations	356	356	306
R-squared	0.3	0.47	0.48
Number of States	51	51	51
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

The lack of a statistically significant effect of immigration on innovation is even more striking when we compare it to closely related studies on the subject. It's the case of the 2003 National Survey of College Graduates, whose data imply that a one percentage point rise in the share of immigrant college graduates in the population increases patents per capita by 6% or Hunt and Gauthier-Loiselle who find that one percentage point increase in the share of the population composed of immigrant college graduates is associated with a 1215% increase in patenting per capita.

One hypothesis that could explain the disparity between results is that net inter-regional migration as defined by the OECD includes all types of migrants moving from one state to another. This includes retired people, university students and children. The contribution of inactive population groups to patenting is less obvious than in the case of college graduates coming into the United States for work purposes. A more interesting hypothesis is that it is the skills that immigrants bring and their educational attainment, in particular in STEM subjects is what drives increases in innovation. Since only a fraction of the people included in my inter-regional migration variable possess those skills, then overall numbers will be less strongly associated to patenting. Unfortunately the available data on inter-state mobility says nothing on the particular skills set of the immigrants, so this study won't be able to shed some light on the question. However this could be an interesting topic for further research.

Before we move on to the instrumental variables estimation results, I will present some further evidence of the validity of the instruments that I am using: the past 1 year and 2 years values of inter-regional net migration. Firstly I test for serial correlation in my model using the test outlined in Wooldridge (2002). Table 3 in the Appendix displays the result of the test, whose null hypothesis is the absence of serial correlation in our model. We cannot reject the null hypothesis at the 20% significance level, which is encouraging evidence that our model is free from serial correlation. Secondly I carry out the Sargan-Hansen test of overidentifying restrictions. The purpose of this test is to test for the exogeneity of our instruments (Bhargava, 1991). Description and results of these tests are available in the Appendix Table 3.

I now proceed to report the results of instrumental variables estimation. Table 4 presents 3 columns. For comparison, I have reproduced the results of the base specification of my model in the first column, as they appear in column 2 of Table 1. The second and third columns show the IV estimation results. The second column shows the results of using only 1 lag of net migration as an instrument for current net migration. The third column shows the results of using both the 1st and 2nd lags as instruments. The coefficients for inter-regional net migration under instrumental variables are still positive but insignificant. The coefficients and standard errors on the control variables are very similar to the within estimator case. The estimates for the effect of the educational attainment variables seem particularly robust to the different specifications. The instruments are strong in the first stage, as indicated by the F-statistic of 32 for the instruments' joint significance test in the first stage (when 2 instruments are used), and by the F-statistic of 53 for the 1 lag instrument in the first stage, when one instrument is used. The first stage itself is shown in Appendix Table 5.

Table 4: Effect of inter-regional migration on log patents per capita, IV specifications

	(1) Base specification	(2) Time dummies	(3) Lagged Covariates
Net Inter-regional migration	0.015	0.01	0.04
Number of permanent residence cards awarded/po	-0.07	-0.04	0.0804
% of workforce with tertiary education	2.9**	2.23*	-1.04
% of workforce with secondary education	2.93**	2.28	-1.03
% of workforce with elementary education	3.02**	2.25	-1.07
Gross R&D investment/GDP, x100	-0.03	-0.01	0
Log of GDP per capita	1.03**	0.63	-0.28
Year Dummies (2011 baseline)			
2005		0.23***	
2006		0.29***	0.26***
2007		0.19***	0.19***
2008		0.02	0.03
2009		-0.03	-0.06*
2010		-0.06*	-0.1***
Constant	-299.7**	-229.4	110.8
Observations	356	356	306
R-squared	0.3	0.47	0.48
Number of States	51	51	51
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

In Appendix Table 6 I check the robustness of the results to different samples and specifications. For conciseness I will only report the coefficients on inter-regional net migration. The first column shows the within estimator results while the second column shows the IV results, using two instruments. In the second row I add seven dummies which represent BEA (Bureau of Economic Analysis) regions and interact them with a time trend in order to capture specifical regional trends in patenting per capita. The coefficient on net migration is still insignificant. In fact, standard errors for this coefficient have almost doubled in this new specification. In row three I introduce state specific trends, which don't bring any substantial changes to either the coefficients or the standard errors compared to the previous specification. In row four I go back to my baseline specification and exclude California from the sample. California's large relative size, high patenting per capita and the presence of Sillicon Valley are reasons to treat it as an outlier. The results seem robust to this new specification. Finally, my period of study (2005-2011) can be divided into two halves before and after the 2008 financial crisis, which has caused a negative structural break in the level of patens per capita. Rows five and six show the coefficients of interest for samples restricted to pre-2008 (2008 not included) and post-2008 observations. Note that the coefficient in row 6 column 1 for net migration is negative and significant at the 5% level . The estimated coefficient implies that a 1 percentage point increase in net inter-regional immigration measured as a percentage of current state population causes a 0.12 percent decrease in patents per million inhabitants. This odd result is to be taken with caution as it is not replicated in the IV specification: the coefficient on net immigration becomes insignificant again.

In Appendix Table 7 I report the interesting response of the coefficients on the tertiary educational attaiment variable and the log of GDP per capita to the same robustness tests. As for net immigration, the results are robust even when BEA dummies and state dummies are interacted with a trend and introduced in the model. Excluding California causes the coefficients of the education attainment variables to drop, and the log of GDP becomes insignificant altogether. Finally the coefficients on the education variables become insignificant when the sample is divided before and after 2008, an log of GDP seems to be the only relevant factor that explains patenting with a coefficient of 1.93 and 1.78 which are higher than in the majority of specifications.

6 Evaluation

As I mentioned earlier, these results are in marked contrast with the previous literature on the topic, which includes Peri (2007) and Borjas and

Doran (2012). Even though the studies arrive to very different conclusions, and they measure knolwledge production in different ways, both find immigration to have a significant effect on innovation. There are several reasons why my results have to be taken with caution.

Firstly, due to lack of data my analysis is limited to the period that goes from 2005 to 2011. Hence I am not able to identify any long run effects of internal moblity on patenting per capita. This problem is exacerbated by the choice of instruments. Since I am using the 1 and 2 period lags of the immigration variable two periods of observations are lost.

Secondly, although I find no evidence that higher inter-regional net migration causes higher patenting per capita, this is not quite the same as the relationship between interstate mobility and innovation since the latter is inherently hard to measure (Grilliches, 1990). This study does not weight each patent by citations in that patent's class, which is a common measure of the 'quality' of the innovation. In addition, it could be the case that more immigrants do increase innovation measured as the number of scientific articles, or the number of technological spinoffs created. Finally, it is possible that immigrants from other US states do cause an increase in innovation that is unmeasurable altogether.

7 Extensions

The results of this study point out to two interesting lines of research that can be pursued in the future. The first one involves restricting the analysis to those internal migrants who are part of the active popluation and sorting them out by skills level or educational attainment. This would solve one of the main limitations of this study in the sense that active and educated people are more likely to make a significant contribution to the innovation that takes place in a state. The second one involves directly looking at the origin of the inventors, and estimating a model of the probablitity of submitting a patent application to measure the patenting gap between inventors native to the state and inventors coming from other states.

8 Conclusion

In this project I have used aggregate data to measure the impact on innovation of inter state mobility across U.S. States in the period 2005-2011. My results show that, in contrast to related studies in the subject, there is no evidence that higher immigration into a particular state causes an increase in patenting per capita. The estimated coefficients are not significantly different from zero. Hence this study finds no evidence for the falling rate of patents per capita in the US, which decreased by 12.5% between 2005 and 2011 to have been caused, even partially, by the decreasing rate of inter regional mobility in the same period. In order to adress potential endogeneity concerns, I have used an instrument for my immigration variable that had not been used previously by the literature: past 1-period and 2-period lags of the immigration variable itself. The results of the IV estimation also do not indicate any kind of relationship between inter state migration and innovation.

However, the educational attainment of the population is found to be the main determinant of patenting. In particular, this study finds that a 1 point increase in the percentage of the labour force that is in possession of either elementary, secondary or tertiary education is associated with a 3% increase in patent applications per million inhabitants. An interesting line of research, that has been impossible to carry out due to lack of individual data on immigrants and inventors, would be to study the impact of inter regional mobility of skilled migrants and compare it to non skilled migrants.

References

Bessen, James and J.Meurer, Michael. 2014. ”The Direct Costs from NPE Disputes”,. Cornell L. Rev. 387, p.99

Bhargava, Alok. 1991. ”Identification and Panel Data Models with Endogenous Regressors,” Review of Economic Studies, Oxford University Press, vol. 58(1), pages 129-140.

Borjas, George J. and Doran, Kirk (2012) ”The Collapse of the Soviet Union and the Productivity of American Mathematicians” NBER Working Paper No. 17800

Bottazzi, Laura Peri, Giovanni, 2004. ”The Dynamics of RD and Innovation in the Short-Run and in the Long-Run,” CEPR Discussion Papers 4479, C.E.P.R. Discussion Papers.

Card, David. 2012. ”Comment: The Elusive Search For Negative Wage Impacts of Immigration.” Journal of European Economics Association.

Falk, Martin. (2007). ”What Determines Patents per Capita in OECD Countries?” Problems and Perspectives in Management / Volume 5, Issue 2.

Furman, Jeffrey L., Porter, Michael E. and Stern, Scott, (2002), The determinants of national innovative capacity, Research Policy, 31, issue 6, p. 899-933.

Griliches, Zvi, 1990. ”Patent Statistics as Economic Indicators: A Survey,” Journal of Economic Literature, American Economic Association, vol. 28(4), pages 1661-1707, December.

Hall, Bronwyn H. 2005. Exploring the Patent Explosion. Journal of Technology Transfer, 30 (1/2) pp. 3548.

Hingley, Peter and Park, Walter G. 2017. ”Do business cycles affect patenting? Evidence from European Patent Office filings”. Technological Forecasting and Social Change, 116, issue C, p. 76-86,

Hunt, Jennifer, and Marjolaine Gauthier-Loiselle, (2009)."How Much Does Immigration Boost Innovation?", American Economic Journal: Macroeconomics (2008).

Jung, D., Wu, A. and Chow, C. W. 2008. Towards understanding the direct and indirect effects of CEOs' transformational leadership on firm innovation. The Leadership Quarterly, 19: 582-594.

Kaplan, Greg and Wohl, Sam. 2015. "Understanding the Long-Run Decline in Interstate Migration". Federal Reserve Bank of Minneapolis, Working Paper 697. p. 5-6.

Kerr, William and Lincoln, William. 2010. "The Supply Side of Innovation: H-1B Visa Reforms and US Ethnic Invention". NBER Working Paper No. 15768

OECD (2016). OECD Stat. (database) Accessed on 30th november 2016.

Peri, Giovanni. 2007. Higher Education, Innovation and Growth. In Giorgio Brunello, Pietro Garibaldi and Etienne Wasmer eds. Education and Training in Europe, Oxford: Oxford University Press.

Romer, P.M. , 1990. "Endogenous Technological Change", Journal of Political Economy 98, 1990, 71-102.

Ulku, H., "RD Innovation and Economic Growth: An Empirical Analysis", IMF Working Paper 04/185, 2004.

Yearbook of Immigration Statistics: 2011. Washington, D.C.: U.S. Department of Homeland Security, Office of Immigration Statistics, 2012

Wooldridge, Jeffrey M. 2002. "Econometric analysis of cross section and panel data". Cambridge, Mass: MIT Press, p.282-283.

A Appendix

A.1 Data and Statistics

The dataset used for this paper is a combination of various independent sources of data. Data on patents per capita, net inter-regional migration and the majority of controls has been taken from the OECD regional statistics database (2016). Data on the number of permanent residence cards issued in each state was obtained from Yearbook of Immigration Statistics (2011)

Table 1: Means of aggregate variables

	(1) 2005-2011	(2) 2005	(3) 2011
Patents/million inhabitants	124.22	137.74	120.43
	(96.7)	(105.77)	(95.84)
Net inter-regional miration/population, x100	0.03	0.06	0.02
	(0.4)	(0.5)	(0.17)
Number of permanent residence cards awarded	21740.64	21952	20761.31
	(41721.35)	(41478.47)	(39169.55)
% of workforce with elementary education	13.92	14.9	12.84
% of workforce with secondary education	61.1	60.44	61.37
% of workforce with tertiary education	25	24.65	25.78
Gross R&D investment/GDP, x100	2.31	2.23	2.34
	(1.59)	(1.57)	(1.56)
State income per capita (constant US dollars, PPP)	43963.22	43115.02	44526.51
	(17111.4)	(16285.98)	(17607.46)
Observations	357	51	51

A.2 Intermediate Results

I use the Wooldridge (2002) and Sargan-Hansen tests to provide evidence for the validity of my intruments. The auxiliary regression for the Wooldridge test is:

$$\hat{e_{i,t}} = \hat{\rho} e_{i,\hat{t}-1} + v_{i,t} \tag{2}$$

Where $e_{i,t}$ are the extracted residuals from a fixed effects regression of patents on net-migration and a vector of covariates.

Table 3: Summary of tests for the validity of the instruments

Wooldridge test for serial correlation (2002)
• H0: $\rho_1 = 0$ (absence of serial correlation in our model) • Ha: $\rho_1 \neq 0$. The errors exhibit serial correlation. • The test statistic obtained is: F(1 , 50) = 1.448 • The p-value is: 0.2346 • The conclusion is: we do not reject H0: our model is free from serial correlation.
Sargan Hansen test for overidentifying restrictions
• H0: H0 overidentification restrictions are valid. • Ha: H0 overidentification restrictions are not valid. • The test statistic obtained is: $\chi2(1)$= 0.372 • The p-value is: 0.5422 • The conclusion is: we do not reject H0: This is evidence that our instruments are exogenous.

Our Instrumental Variables model estimates the equation:

$$\log \frac{P_{i,t}}{Pop_{i,t}} = \gamma_0 + \gamma_1 \widehat{N_{i,t}} + \gamma_2 X_{i,t} + \sum_{t=2005}^{2011} c_t + u_{i,t} \tag{3}$$

Where $\widehat{N_{i,t}}$ are the fitted values from the first stage regression of $N_{i,t}$ on the instruments $N_{i,t-1}, N_{i,t-2}$:

$$\widehat{N_{i,t}} = \gamma_0 + \gamma_{1i,t-1} + \gamma_2 N_{i,t-2} + \delta X_{i,t} + u_{i,t} \tag{4}$$

Table 5: First stage regressions

	(1) 1 instrument	(2) 2 instruments
Net Inter-regional migration, 1-Period Lag		0.36***
Net Inter-regional migration, 2-Period Lag	0.41***	0.12**
Number of permanent residence cards awarded/population, x1000	0.55***	-0.18
% of workforce with tertiary education	0.22	-2.17
% of workforce with secondary education	0.23	-2.12
% of workforce with elementary education	0.22	-2.05
Gross R&D investment/GDP, x100	-0.09	-0.03
Log of GDP per capita	0.2	0.92
Year Dummies (2011 baseline)		
2005	-	-
2006	-	0.33***
2007	0.08	-0.15*
2008	0	-0.13*
2009	-0.02	-0.05
2010	-0.03	-0.08*
Constant	-0.03	204.1
Observations	356	254
R-squared	0.3	0.314
Number of States	51	51
Robust standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

A.3 Robustness

Table 6: Effect of net inter-regional migration on log patents per capita, further specifications

	(1) Within Estimator	(2) IV, 2 instruments
Base Specification	0.01	0.04
Include BEA region time trends	-0.001	-0.01
Include state specific time trends	0.02	0.02
Without California	0 .012	-0.003
Observations until 2008	0.001	-0.14
Observations after 2008	-0.12	0.04
*** p<0.01, ** p<0.05, * p<0.1		

Table 7: Effect of net inter-regional migration on log GDP per capita and % of workforce with tertiary education, further specifications

	Coefficients on % of workforce with tertiary educ.		Coefficients on % of log GDP per capita	
	(1)	(2)	(1)	(2)
	Within Estimator	IV, 2 instruments	Within Estimator	IV, 2 instruments
Base Specification	0.01	0.04	0.63	-0.28
Include BEA region time trends	3.07**	3.4*	1.22***	1.49***
Include state specific time trends	1.62	2.72	1.96***	1.92***
Without California	2.56*	2.99*	0.63	0.4
Observations until 2008	0.53	5.9	0.76	-0.37
Observations after 2008	1.52	1.89	1.93**	1.78**

*** p<0.01, ** p<0.05, * p<0.1