Senior Project

Department of Economics

"Surging Innovation through Emerging Immigration"

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Abstract

This paper estimates the effect of skilled immigrants on innovation measured by patent activity in European countries. I use a sample of 22 OECD countries with observations from 2000 and 2005. The OLS estimate shows that a 1 percentage point increase in the level of tertiary education of immigrants will increase patents per million inhabitants by .927%. But, tertiary education parameter for immigrants (zkf) is not significant with a P-Value of 0.654. This is largely due to the data limitation of skill level of immigrants to two years (2000 & 2005). Using the Fixed-Effect model, the significance only improves slightly and reveals that the countries itself are highly correlated with the patent activity. Overall, better availability of education data for immigrants should boost the significance of the parameter estimates. To further enhance the results of this work a Two-Stage Least Square approach is needed to control for the endogenous variables skill level and GDP growth.

I would like to thank Dr Renna for reading my paper and helping me during my research. I would also like to thank Dr Erickson & Dr Nelson for reading my paper and making necessary corrections.

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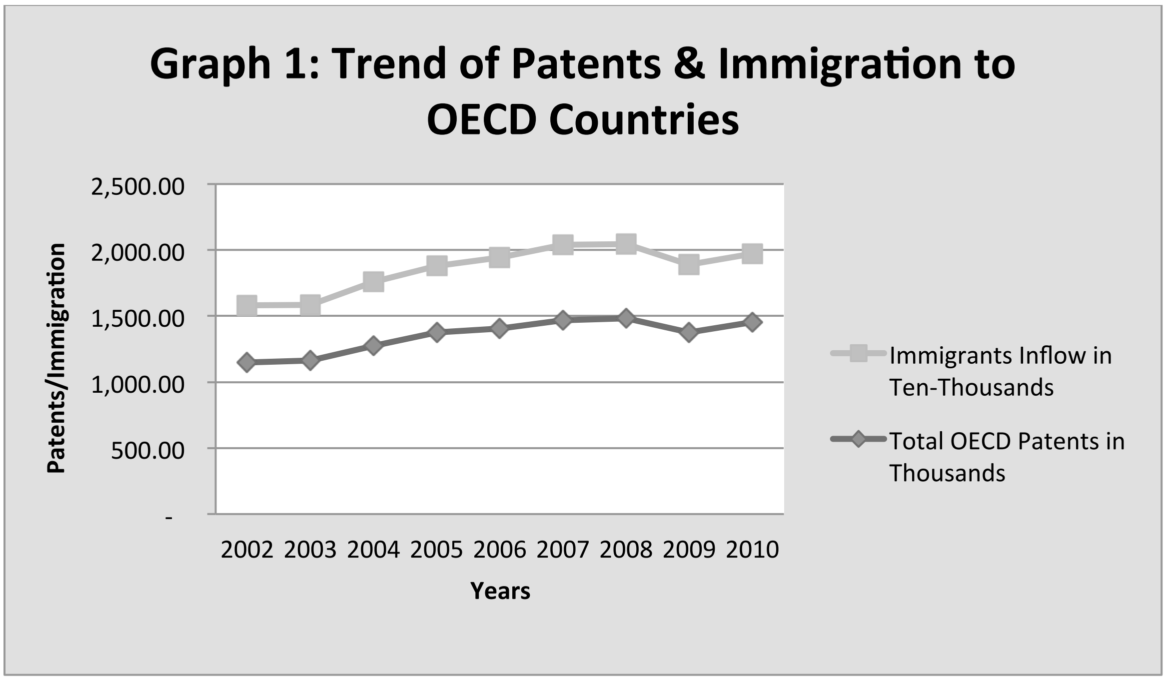
1. Introduction

Immigration to OECD countries has been on the rise since the beginning of the 2000s reaching a high of 20 million in 2007 (OECD 2014) and patent activity has experienced similar growth and peaked at almost 1.5 million patents filed in (WIPO 2014). The rise in immigration and patents in OECD countries is very similar, see graph below.



Source: OECD Migration Database/WIPO Statistics Database

The graph shows a positive correlation between patents and immigration over a time span of almost 8 years. My analysis is trying to determine if the immigration inflows had a positive effect on the patent activity. The increased human capital stock due to immigration is part of several recent studies observing the impact of immigration on innovation using patent applications. The expected positive effect on innovation is facilitated through an inflow of immigrants which increases the diversity and knowledge pool within a country. Foreigners in

OECD countries have a diverse cultural background and offer different point of views. Hence, a breeding ground for research is built and will enable patent applications.

Immigration has been a topic of interest for many studies in economics analyzing the impact on population growth (Drinkwater, et al. 2007), skill upgrading (Ortega 2005), wage levels (Barcellos 2010), rent seeking (Powell 2012), tax revenue and expenditure (Rowthorn 2008) as well as ethnic diversity (Polachek, Carnel and Rupport 2006). The most recent topic of interest is the impact of immigration on innovation. The economic literature is still in its infant stage on this topic, providing only a few studies. Some studies incorporate patent data as the independent variable (Ozgen, Niklamp and Poot, Immigration and Innovation in European Regions 2011) while other use R&D data (Niebuhr 2009). The independent variable for immigration covers a range of variables from individual- (Niebuhr 2009) to city- (R. Kerr and F. Lincoln 2008), firm-level (Mare, Fabling and Stillman 2011), to economic regions (Ozgen, Niklamp and Poot, Immigration and Innovation in European Regions 2011).

The aim of this study is to analyze the overall impact of immigration to OECD countries on patent registrations. This study differentiates itself from prior studies by focusing on immigration flows to OECD countries as a whole. *Table 2: OECD Country Map* shows in detail which OECD countries were included. In addition, further emphasis is placed on the skill level of immigrants. Prior studies have neglected skill-related data or estimated the educational attainment through complex proxies that did not yield high significance in the regression modeling. Since OECD countries have a tremendous inflow of immigrants from developed and other countries worldwide, the skill level can be a differentiating factor of how immigration effects innovation.

2. Literature Review

Hunt & Gauthier-Loiselle (2010) as well as Kerr & Lincoln (2008) focus on the impact of skilled immigration, in the form of immigrant graduate students and H1-B Visa-holders respectively, on innovation in the United States. Higher concentrations of patenting activity appear in the science and engineering (SE) sectors according to Hunt et al. (2010). Hunt & Gauthier-Loiselle (2010) observed that a 0.45 percentage point increase in immigrants in the SE field increases patents per capita of 13%. Similarly, Kerr & Lincoln (2008) show that a 10% increase in SE immigrant population leads to 1.6% increase in total patent population. Also, Hunt and Gauthier (2010) find important spillover effect of immigrants on the innovation levels of natives, while Kerr and Lincoln (2008) do not. One possible explanation for the difference in the findings of the two papers is that they proxy skilled immigration differently through graduate students (Hunt and Gauthier-Loiselle 2010) and H1-B visa holders (R. Kerr and F. Lincoln 2008).

Hunt & Gauthier-Loiselle (2010) are able to find a clearer spillover effect on the native population by compering individual-level data from the National Survey of College Graduates (NSCG) with aggregate data from the state level. In fact, when they use aggregate state level data they find that a one percent increase in the immigrant share of population increases patents per capita by 12-15%. This increase is double the six percent observed in the individual-level NSCG data. This difference suggests a strong positive spillover (crowding-in effect) effect of immigration to natives in the United States.

In contrast, Kerr and Lincoln (2008) focus on the effect of H-1B visas employees on the patent level measured at the firm and city level in the U.S. They separate their firms sample into two groups firms that depend on H-1B visa and firms that do not relay on H-1B visa. Similarly they separate cities in five quintiles based on their dependency on H-1B visas. When firm-level data is utilized, an increase of 10% of H-1B holders increases Indian immigrant patenting in the U.S. computer industry by 8%   relative to the less-dependent half of the computer industry. But, the native patenting activity within computer-related firms is not positively affected by an increase in the H-1B visa level. This robustness check with firm-level data reveals that the crowding-in effect observed with city-level data is not existing. When city level data are utilized, the H-1B program increases Indian patenting activity by up to 10% in cities that are in the most dependent quintile. .

Similarly to Kerr and Lincoln (2008), Niebuhr (2009) provides evidence on the impact of migration on innovation by employment data, but focuses on Research and Development (R&D) staff and expenditures instead of patents in Germany. Likewise, Mare et al. (2011) use employment data from a longitudinal business database in New Zealand. They merge it with New Zealand Census data to examine firm-level innovation outcomes and the composition of the regional workforce in New Zealand.

Niebuhr (2009) and Mare et al. (2011) both conclude that Research and Development (R&D) is the most important factor to predict innovation levels. Niebuhr predicted that a 100% increase in R&D employment in Germany would increase patents per capita by 34%. Mare observes that the 7% of businesses that report positive R&D expenditure in New Zealand are 36% more likely to introduce new goods and services.

In contrast, Niebuhr (2009) also shows that a 100% increase in diversity, measured as a share of certain nationalities within the R&D population, would increase patents per capita by 24%. Mare is not able to show any significance of a culturally-diverse workforce on the creation of new goods and services. The conclusions of both papers are contradictory and display the lack of consensus in countries outside the U.S. on what facilitates increased innovation activity.

This contradiction is described by Ozgen et al. (2011) as the indirect influence of immigration. Immigrants bring through their inherent cultural diversity, a different view-point. This difference between natives and immigrants build the contextual framework. It is a melting pot for innovation. The evidence for the contextual framework is the strong correlation between the control variables (industrial composition, GDP growth, human resources in science and technology) and innovation.

Ozgen at al. (2011) research found that the cultural diversity of a regional population positively influences patents activity. An increase of 1 percentage point in the diversity index increases patent applications per millions by 0.16%. Although he was unable to find a direct effect of the share of immigrants on patent activity, similar to Niebuhr (2009) and Mare et al. (2001), the cultural diversity index describes immigration as being a breeding ground for innovation. This assumption was made before by Niebuhr (2009) and Mare (2001), but the data was insufficient. Ozgen et al. (2011) use aggregated data for 170 business regions in 12 European countries instead of firm-level data.

Overall, the existing literature has been evaluating immigration and innovation with different data sets. Every reviewed paper had a similar conclusion: skilled immigration creates a positive contextual environment for patents within a country. One aspect of the immigration data was always mentioned, but usually not clearly defined: the level of skilled immigration. H1-B visas (R. Kerr and F. Lincoln 2008) or R&D staff (Niebuhr 2009) were used as proxies but did not define the skill level of immigrants closely. Ozgen et al. omitted the skill variable completely. With this paper I seek to fill this gap and use data on the skill level of immigrants in OECD countries in place of proxy variables.

3. Empirical Model

This project is aimed at testing if immigrants of different educational backgrounds have a positive effect on innovation by measuring patent applications. The hypothesis is: *The higher the skill level of immigrants moving to each OECD country (see Table 1), the number of patents per million inhabitants will increase.* Immigration will be defined similar to Ozgen et al. (2011) model which is described in the next section.

This paper will demonstrate the effect of immigration on patent application in OECD countries by using a model similar to Ozgen et al. (2011) established model. The model describes that immigration may influence innovation through three different channels:

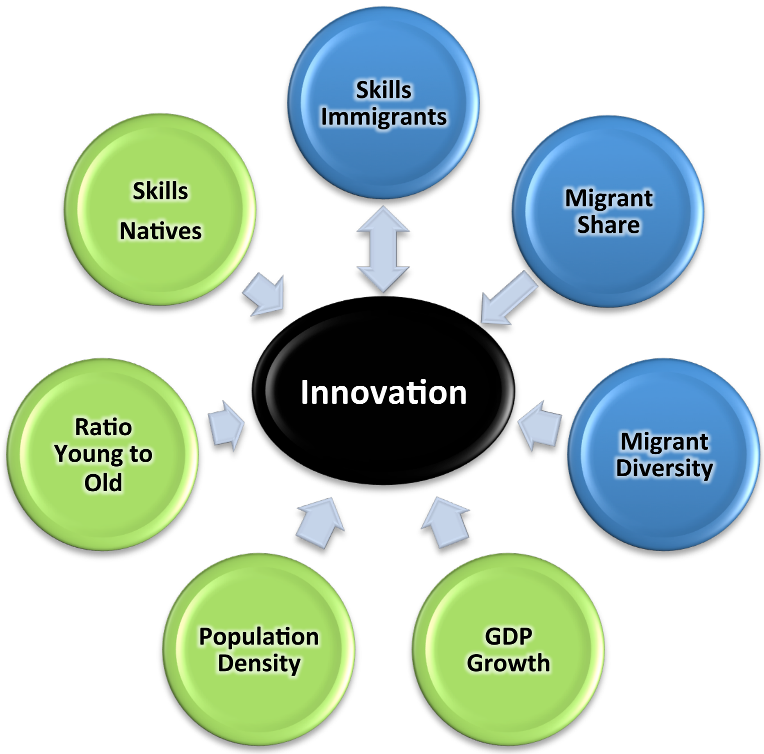
I. Skill Composition

II. Migrant Share as a total of the population

III. Migrant Diversity (Source Country/Region)

The two additional effect of population are related to the overall population size and population density and are included as fourth and fifth independent variable relating to population in Ozgen et al. (2011) model.

Graph 1: Economic Theory



Immigration has been described by several studies including Ozgen et al. (2011) as an endogenous variable in relation to innovation. The two-way causality is demonstrated by the two-headed arrows in the *Theoretical Model* above for Migrant Share and Skills of immigrants. Ozgen uses the distribution of McDonald's restaurants to successfully control for this endogeneity. I am unable to control for the endogeneity because of the lack of data.

Whereas Ozgen et al. (2011) omits the skill composition, I am including the skill composition with data from 2000 & 2005 census data gathered by the OECD. Immigration can be differentiated into three different educational attainment levels (primary, secondary, tertiary).

I am focusing on the tertiary education which is equivalent to university education and is expected to have the greatest effect on innovation.

The econometric model will be run as an ordinary-least square (OLS) regression. Ozgen et al. (2011) results of the two-stage least-square have not shown significant improvements over the OLS regression. I will also run a fixed effect model to utilize all the data given in the panel data set.

Econometric Model:

$$\boldsymbol{Pat} = ß_0 + ß_1\boldsymbol{Shfor} + ß_2\mathbf{Pd} + ß_3\boldsymbol{Zkf} + ß_4\boldsymbol{Zkd} + ß_5\boldsymbol{Frac} + ß_6\boldsymbol{GDPgr} + ß_7\mathbf{Ratio\_YO} + ß_7\mathbf{Ctry\_Dy} + \varepsilon \quad (1)$$

Pat is the dependent variable measured in patents per million inhabitants as an average over two years (2001/2002 & 2006/2007). The use of a two year average is useful because of missing data or inaccurate measurement. In addition, the longer time period is more desirable because immigration will not affect innovation within the first year, but rather over several years (Ozgen, Niklamp and Poot, Immigration and Innovation in European Regions 2011). The combination of the patenting data with the population data includes the effect of population on patent activity. Therefore, the variable population has been removed from the model to avoid multicollinearity.

Shfor is the first independent variable measuring the share of foreigners in relation to the total population. This variable is part of Ozgen et al. (2011) model and is the first of three ways that immigration affects innovation. Although this variable can be potentially endogenous, Ozgen et al. (2011) was not able to show a significant improvement after controlling for endogeneity. Therefore, I am assuming the variable is exoneous. The expected effect on patent application is positive: The higher the share of foreigners, the greater the pool of ideas and knowledge.

The variable *Pd* is the population density per square kilometer. Ozgen et al. (2011) used this variable to support patent application. More inhabitants provide a larger pool of knowledge and ideas and are expected to have a positive effect on innovation. In addition, the density of the population creates more interactions and facilitates exchanges through communication. This is also expected to positively influence innovation.

Zkf is the tertiary education of immigrants and was omitted by Ozgen et al. (2011). Data from a labor survey in 2000 and 2005 is published on OECD migration database and displays the immigrants to OECD countries by educational level. This variable is crucial to the current analysis as it has not been used but often cited in the literature. Immigrants fall into this category by having more than 18 years of education. The effect of tertiary education on innovation is expected to be positive. I excluded primary and secondary education because the time spend in school by immigrants in this category is not enough to warrant patent-level research. Therefore, primary and secondary education of immigrants can be found in the intercept.

Zkd is the tertiary education of native workers. Education for domestic workers is equally important because it can also positively contribute to the patent activity within a country. Omitting this variable will decrease the explanatory power of my model. Primary and secondary education are excluded again because also domestic workers will not have enough skills to perform patent-level research. Therefore, domestic primary and secondary education can be found in the intercept as well.

Fra is the fractionalization index (Alesina, et al. 2003) measures the immigration diversity. It excludes native-born population to eliminate multicollinearity with the share of immigrants for each country. The fractionalization index is calculated as follows:

$$Fra_j = 1 - \sum_{i=1}^{N} s_{i,j}^2 \quad (2)$$

In which $s_{i,j}$ is the share of immigration from each OECD country i (i=1,….,N) in each sample country j. The index shows the probability of two randomly selected people belonging to different population groups. The index values range from 0 to 1-1/N. The classification of population groups is based on the UNESCO Region Classification: Africa, Arab States, Asia/the Pacific, Europe/North America as well as Latin America/Caribbean. The more diverse the OECD country, the higher are innovation level. Ozgen et al. (2011) in "The Impact of Cultural Diversity on innovation: Evidence form Dutch firm-level data" supports this theory and shows that local firms that employ more immigrants are more innovative.

GDPgr shows the growth of the GDP for each OECD country and has shown a positive effect on patent activity in models including Ozgen et. al (2011). The larger the growth of GDP in each OECD country is, the larger the increase in patent activity.

The *Ratio_YO* represents the ratio of the young population 24-44 years old to the total population 24-64. The is ratio has been used by Ozgen et al. (2011). The bigger the younger population compared to the old population, the higher the expected positive effect on innovation in that country. Acemoglu et al. (2014) recently showed that companies with younger managers tend to have more disruptive patents measured by total citations in the academic literature.

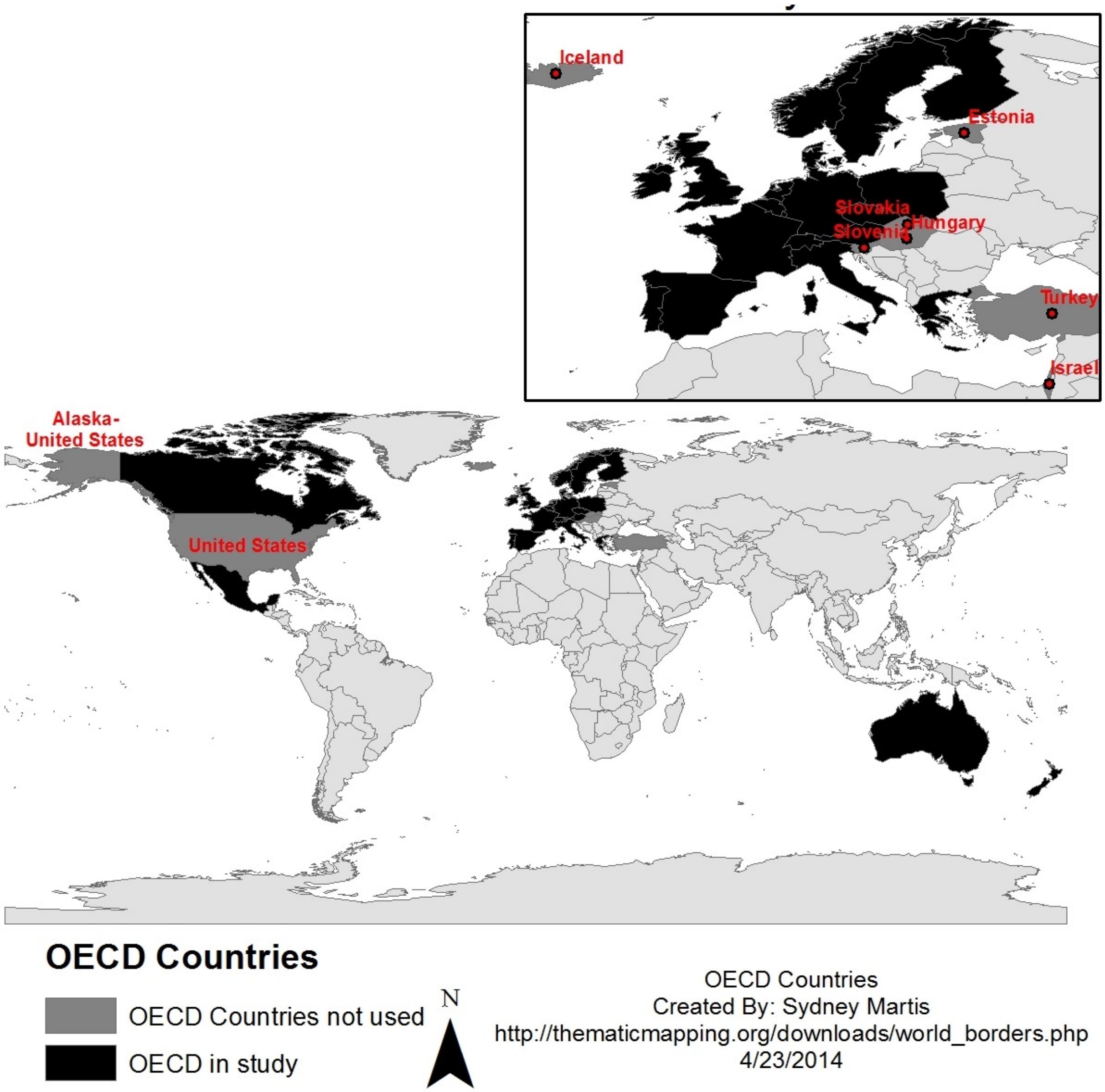
Ctry_Dy variable summarizes all the country dummy variables used in the fixed effects model. Since I use a panel dataset, the OLS does not take full advantage of the data given. The fixed effect also incorporates the OECD countries I collected data for.

Overall, this project will try build on previous studies observing immigration effect on innovation by using educational attainment levels to evaluate the skill level of immigrants. The econometric model was established by Ozgen et al. (2011) and is used in a similar form in my study.

4. **Data**

While working on the quantitative estimation in this paper I encountered several problems with the data. The limiting factor in my data set is the availability of skill level data for immigrants in OECD countries. There has only been one survey administered by the OECD in 2000 asking immigrants in several OECD countries about the skill status. A small follow-up survey was done in 2005. Combining both gives me a sample size of 44. In addition, the lack of certain data for the remaining OECD countries eliminated several of those countries.

Table 2: OECD Country Map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United States
United States
OECD Countries
OECD Countries not used
OECD in study
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OECD Countries
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Table 3: Variable Description

Variable	Variable Description	Variable Source
Log(Pat)	Total patent applications averaged over 2 years per million inhabitants (%) (2001/2002 - 2006/2007) [-.76; 6.10]	*EPO*
Shfor	Share of new immigrants coming to the country of the total population (%) (2001 & 2005) [.000062; .030042]	*Eurostat, OECD Migration Statistics*
Pd	Population Density (total pop/km2) (2000 & 2005) [.002; .39]	*Eurostat*
Zkf	Tertiary Education: 18 years of schooling (%) (2000 & 2005) [.112; .474]	*OECD Migration Statistics, own calculations*
Zkd	Tertiary Education (%) (2000 & 2005) [.090; .460]	*Barro-Lee Educational Attainment Dataset*
Fra	Fractionalization Index = 1 – Herfindal index of nationality shares (2000 & 2005) [.13; .75]	*OECD Migration Statistics; UNESCO Region Classification*
Ratio_YO	Ratio of population aged 25-44 over population aged 25-64 (2000 & 2005) (%) [.48; .69]	*OECD Migration Statistics*
GDPgr	GDP growth rate (%) (2000 & 2005) [-3.50; 9.10]	*OECD Statistics*
Country Dummy Variables*	See Table 1 for all countries included	*Own Calculation*

**Only Used in Fixed Effect Models*

Table 4: Descriptive Statistics describes the spread of the data as well as the mean and standard deviation. The standard deviation for skilled immigrants at the tertiary level (zkf) as well as the skilled domestic workers at the tertiary level (zkd) is very similar. Both variables are not concentrated and are suitable for regression analysis. All the country dummy variables have the same values due to their inherent nature of either being one or zero. The same is valid for the year 2000 and 2005. The dummy variables are only used in the Fixed-Effect model.

Further, I checked the skill variables for outliers and correlation. No extreme outliers have been detected. The correlation between the skill variables showed no significant results. The correlation between the tertiary education level of immigrants and patents had a correlation of about .20, which suggests that an OLS or other modelling techniques should reveal the correlation.

5. Empirical Results

Most of the results are similar to previous findings while some or not. First, I explain the results from the OLS regression analysis. Second, I will go over the results for the fixed effect estimation.

5.1. OLS Estimation

Table 5: (pg. 27) is supporting most of the theoretical framework, especially the positive influence of skill level of immigrants on patent activity. A 1 percentage point increase in the tertiary skill level of immigrants, boosts patents per million inhabitants by .93 %. Although the positive relationship supports the model, the variable is not significant with a P-Value of .6541. Further modelling is required to increase the significance. (see section 5.2. Fixed Effect Estimation).

Contrary, the skill level of domestic workers shows a negative impact for tertiary education. A 1 percentage point increase in tertiary skill level of domestic workers decreases patents per million inhabitants by 1.2 %. This is contradictory to theory. Education is described as an enabler for innovation, but in the case of domestic tertiary education theory does not hold true.

The fractionalization index is positive and statistically significant, which shows that culturally more diverse societies have a positive influence on patent applications. If the diversity index increases by 0.1 patent applications per million inhabitants increase by 4.41 %. The impact in my OLS estimation is much higher than what Ozgen et al. (2011) estimated.

Furthermore, the share of immigrants in each country has a positive influence on patent applications and is highly significant.

The ratio of young to old people has a negative effect on the patent applications and is highly significant. This can be explained by the raw data revealing that the societies in OECD countries are becoming older. Hence, the ratio is skewed toward older people. Since old people are less likely to innovate than younger people because of less social interaction and risk-taking, the negative impact on patent applications makes sense.

The last two still significant variables are population density and GDP growth. Both display a positive relationship and support the framework set by Ozgen. A 1 percentage point increase in GDP growth would increase patenting per million inhabitants by 0.18%. A population density increase by 1 percentage point is even more impactful and would increase patenting almost 2.46%.

Overall, the OLS estimation returned significant parameter estimates reflecting the high adjusted R-Squared explaining 75% of the variance. The variable of interest, tertiary skill level of immigrants, remains not significant.

5.2. One-Way Fixed Effect Estimations

The one-way fixed effect model (*Table 5:* Regression Results pg. 27) is used in order to control for unobserved heterogeneity. Since I am using a panel data set, the information given in the form of the OECD countries and years cannot be processed in a regular OLS estimation. The one-way fixed effects model uses dummy variables for the OECD countries. I neglected years to be run in a separate one-way fixed effect because the difference to the OLS is very minimal and thus not worth mentioning.

The one-way fixed effect model includes all the country dummy variables and excludes Portugal which is included in the intercept. Although the overall model's adjusted R-squared improved to 0.98, the variable of interest zkf improved only slightly. A 1 percentage point increase in foreign skills of immigrants increases patents per million by 0.74 % at a very low significance level of 0.50. Other variables changed completely and are in conflict with the theory: population density, GDP growth are having a negative impact on the patent activity. The positive effects of the diversity index (frac) and the share of immigrants (shf) have also decreased dramatically.

Overall, the country fixed effect model reveals that the countries seem to have an impact on the model: Denmark being highly significant; Austria, France and Switzerland having slightly smaller significance levels. All countries except Mexico and Poland have a positive effect on the patenting activity. A 1 percentage point increases in Denmark increases patenting activity per million by 3.52%. Countries with a high population density like Denmark, Belgium, Germany and Switzerland have the highest parameter.

6. Conclusion

The OLS estimation has returned more significant results than I expected, but leaves the variable of interest tertiary education of immigrants insignificant. Since I am using panel data from several different OECD countries and two different years (2000 & 2005), the fixed effect should take advantage of the data and improve the significance level of the skill variable.

In contrast, the fixed-effect model turned out to not improve the skill variable at all. The fixed effect revealed that the country itself might play a much bigger role in producing patents than the education of immigrants. Domestic tertiary education even has a negative effect on patent activity.

Immigrants remain important for the innovation levels of OECD countries. The large positive effect of diversity on patenting supports the theory that immigrants create a contextual environment that boosts innovation activity. The larger the pool of differing nationalities, the bigger are the chances of breakthrough immigration.

My model has some shortcomings that can potentially explain the weak effect of education on patent activity including the lack of data. I was limited to two immigrant skill data sets form 2000 and 2005. If earlier and later data would be available the model would contain more observations and therefore increase sample size.

Furthermore, the endogeneity between skills of immigrants and innovation can only be controlled for through a Two-Stage Least Square approach. One possibility would be to use the number of universities in the respective country as an instrumental variable to control for this endogeneity. The lack of data on university limits this approach. Similarly, GDP growth can potentially be an endogenous variable in relation to innovation. This bias is not controlled for in my model and can lead to differing results.

Overall, more advanced econometric modeling techniques including a Two-Stage Least Square approach are needed. Due to the lack of sufficient observations and data for instrumental variables, the Econometric modeling cannot be expanded beyond the OLS and Fixed Effect approach.

7. Works Cited

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Appendix

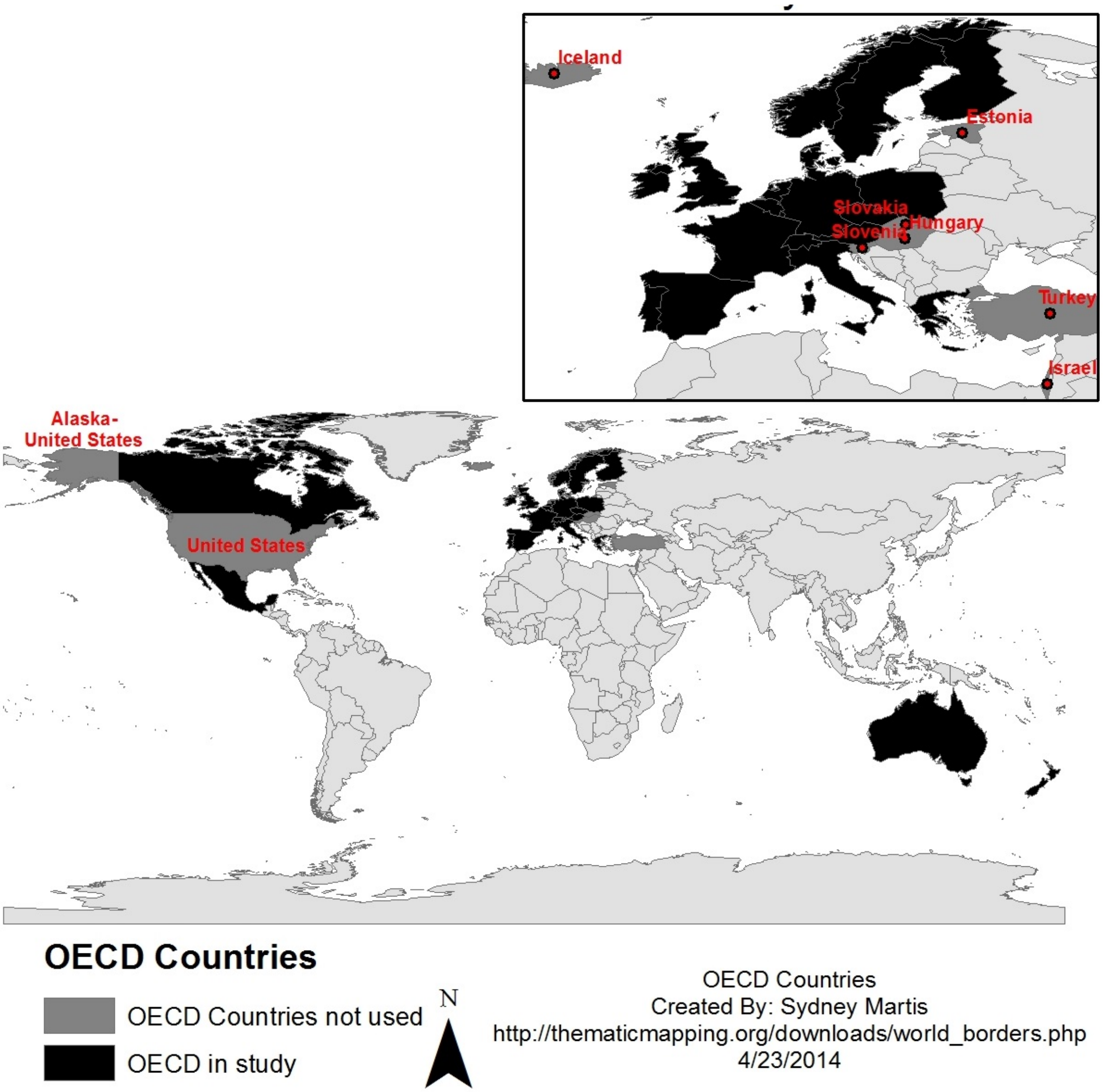
Table 1: Countries in Data Set

Countries Included in the data set[1]

Australia	Germany	Norway
Austria	Greece	Poland
Belgium	Ireland	Portugal
Canada	Italy	Spain
Czech Republic	Luxembourg	Sweden
Denmark	Mexico	Switzerland
Finland	Netherlands	United Kingdom
France	New Zealand	

Table 2: OECD Country Map

[1] All countries are OECD countries. Some countries had to be dropped due to missing values. Australia, Canada, Mexico and New Zealand have been added as non-European countries to increase the sample size


Iceland
Estonia
Slovakia
Hungary
Slovenia
Turkey
Israel
Alaska-
United States
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GDPgr	GDP growth rate (%) (2000 & 2005) [-3.50; 9.10]	*OECD Statistics*
Country Dummy Variables*	See Table 1 for all countries included	*Own Calculation*

**Only Used in Fixed Effect Models*

Table 4: Descriptive Statistics

Variable	N	Mean	Standard Deviation	Min	Max
Ratio_YO	44	0.551	0.036	0.481	0.685
frac	44	0.502	0.192	0.134	0.752
pat	44	4.053	1.696	-0.757	6.105
pd	44	0.124	0.105	0.002	0.392
shf	44	0.007	0.006	0.00006	0.030
zkf	44	0.247	0.086	0.112	0.474
zkd	44	0.202	0.083	0.090	0.460
GDPgr	44	3.357	2.932	-3.500	9.100
Country Dummy	Included for all countries listed under ***Table 1:*** *Countries in Data Set*				

Table 5: Regression Results

Dep.var.: log(Pat)	**OLS**	**One-Way Fixed**
Intercept	14.79	3.96
	(<.0001)	(0.4985)
pd	2.46	-10.86
	(0.0804)	(0.6751)
shf	162.32	51.22
	(<.0001)	(0.1649)
zkf	0.93	0.74
	(0.6541)	(0.5015)
zkd	-1.20	-1.81
	(0.6105)	(0.6220)
GDPgr	0.18	-0.03
	(0.0004)	(0.3223)
Ratio_YO	-27.12	-2.64
	(<.0001)	(0.6966)
frac	4.41	0.93
	(<.0001)	(0.6106)
Country Dummy	No	Yes
N	44	44
Adj. R-Squared	0.75	0.98
F-Test	9.82	