SKILL DIFFERENTIALS BETWEEN VISA CATEGORIES IN THE UNITED STATES

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Abstract

This study focuses on skill differentials between different visa categories in the U.S. and presents the skill distribution of immigrants under family and employment visa categories over time for the first time. Moreover, the study is first to analyze the skill difference of immigrants under family and employment visa categories and shows that the main mechanism behind the skill differential is changing the selectivity of immigrants by choosing more skilled immigrants within region of origins rather than shifting the regional composition of the immigrants. Moreover, it is also shown that selectivity of immigrants affects only employment visa category rather than family visa category confirming the effectiveness of immigration policies towards attracting more skilled immigrants.

AMERİKA'DA FARKLI VİZE KATEGORİLERİNE GÖRE BECERİ FARKLILIKLARI

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Özet

Bu çalismada, farklı vize kategorisinde Amerika'ya gelen goçmenlerin beceri farklarına ve bu farkların nedenlerine odaklanılmaktadır. Amerika'daki farklı vize kategorilerinin zaman içerisindeki beceri farkları ilk defa ortaya konulmustur. Bunun yanı sıra, beceri farklarının nedenleri ilk kez incelenmistir. Bu analizler sonucunda, beceri farklarının nedeninin goçmenlerin bölge kompozisonlarının degismesinden ziyade aynı bölgelerden daha iyi göçmenlerin seçilmesi oldugu bulunmustur. Ayrıca, bu çalisma Amerika'nın daha becerili göçmen çekme doğrultusunda değistirdiği politikalarını da doğrulamaktadır.

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1 INTRODUCTION

Immigration is a controversial subject in the U.S. Supporters see immigrants as a source of human capital, which increases the productivity of the country. On the other hand, according to the opponents, it is seen as a burden on social welfare, since many of the immigrants are low skilled and take advantage of the welfare system. Hence, the net effect of immigration is ambiguous. Since countries decide on whom to accept as an immigrant, immigration policies can be used to overcome the negative effects of immigration.

Countries not only accept immigrants for employment purposes but also for other objectives. Family reunification and humanitarian concerns play important roles in immigration policy. With this regard, it is important to identify the objective of the immigration policy first. In some major immigrant receiving countries, the primary criteria is the skill level. In Canada, for instance, 65% of the visas are allocated for skilled workers, 27% for family class and the rest is allocated based on humanitarian grounds under the points system according to 2000-2001 LSCIS data (Aydemir, 2012). In contrast, the U.S., without having such skill criteria, allocates most of the visas based on family ties using the preference system. Under the preference system, while 80% of visas were allocated based on family ties, 20% were allocated based on skills up until 1990s (Borjas, 1993).

In recent decades, the attention in the U.S. immigration policy centered on selecting more skilled immigrants. By changing the quotas for different visa categories and adding new categories for employment, immigration policy favored more skilled immigrants. However, the effect of this policy changes is not clear.

It is important to address the question of whether the policy changes towards generating a higher-skilled immigrant flow works. Moreover, if the policies work, the channels through which policies generate a higher-skilled immigrant flow is also crucial. These policy changes are expected to effect the visa categories based on skill level (employment visa category for the U.S.). Therefore, comparing the skill levels of employment visa category and family visa category can help to address the ongoing debate on the selectivity of different visa categories and the trade-off between numbers allocated for these visa categories.

This study focuses on skill differentials between family and employment visa categories and how the differences between these two visa categories change over time. To this end, Immigration Naturalization Service (INS) data set is used to extract visa category and country of birth information. The criteria for skilled immigrants is their human capital characteristics which is commonly measured by years of schooling. Hence, we used years of schooling information as a skill measure. There is no information on education in INS data. Using U.S. Censuses, years of schooling information is generated and matched with INS data using the occupational information in both data sets. Matching these data sets; each region and visa category is associated with years of schooling information. In addition, a new data set is generated using International Censuses to confirm the results.

The study has substantial contributions to the literature. First, the skill distribution of the U.S. immigrants under different visa categories over time is presented for the first time. Presenting the skill levels of the immigrants under different visa categories, this study is first to analyze the skill difference for immigrants under different visa categories. It is shown that, the main mechanism behind the skill differential is changing the selectivity by choosing more skilled immigrants within region of origins rather than shifting the regional composition of the immigrants. In addition, the study shows that selectivity of immigrants effects only employment visa category rather than family visa category. Hence, it confirms the expected effects of major immigration policies such as the Immigration Act of 1990 which changed the criteria of employment visa category aiming to increase the skill level. Therefore, the study enables assessment of policy changes as well.

The structure of the paper is as follows: Chapter 2 reviews the previous literature on skilled immigration and points out the studies on analyzing the skill differential. Chapter 3 discusses the data and its complications and how different data sets are merged together to get both visa category and years of schooling data. Chapter 4 discusses the descriptive statistics stating the number of immigrants under each region, visa category and their mean years of schooling. Given descriptive results, Chapter 5 analyzes the skill differential between different visa category. The last chapter concludes by summarizing the main results of the study.

2 LITERATURE REVIEW

The literature on skilled immigration focuses on three major topics. Throughout this chapter; first, the importance of skilled immigration is discussed which is followed by the importance of immigration policies in shaping the skilled immigration. In light of the role of immigration policies, immigration policies of major immigrant receiving countries is discussed next. The last point is the effectiveness of these policies in attracting skilled migrants.

2.1 Importance of Skilled Immigration

Skilled immigration is considered to have important consequences in terms of economic policies and it has economic, social and political impacts for both sending and receiving countries (Castles, Miller, & Ammendola, 2005).There has been a burgeoning literature on the consequences of skilled immigrants both for developed and developing countries due to its welfare implications, economic impacts and long term human capital impacts(Docquier & Rapoport, 2007; Bhagwati & Hanson, 2009; Batalova, 2006; Constant & Zimmermann, 2013; Commander, Kangasniemi, & Winters, 2004).

It has been argued that low-skilled immigrants impose higher costs to the welfare system by paying less taxes and benefiting from the public services more (Borjas, 2001; Borjas & Hilton, 1996; Fix, 2002). On the other hand, high skilled immigrants are considered to have positive fiscal contributions by paying more taxes and widening the tax base which indirectly decreases the old age dependency ratio. (Aydemir, 2012).

There is a strand of literature analyzing the effects of high skilled immigration on innovation and growth (Hunt, 2009; Hunt & Gauthier-Loiselle, 2008; Kerr & Lincoln, 2010). It is shown that skilled immigrants boost inovation and growth. Hence, developed countries try to attract the highest skilled group; best graduate students and workers brown2006assimilation. Moreover, Bhagwati et al. (2009) argues that, the high skilled population in developing countries have a higher tendency to migrate. Borjas (2006), Hansen

(2006), Iqbal (2000), and Mahroum (1998) show that U.S. is attracting high skilled workers from developed and developing countries. In response to that loss, China gives incentives to attract skilled immigrants as well (Constant, Tien, Zimmermann, & Meng, 2013).

Migration of high skilled workers form Africa, Asia, Latin America to developed countries raises discussions about ”brain gain” and ”brain drain”. The advantages of brain gain to receiving countries is discussed by Stark et al. (2002; 1997). On the other hand, Mountford (1997), Stark at al. (1997), Baine et al. (2001) and Docquier et al. (2011) discuss the positive effects of brain drain on sending countries. However, there are disadvantages of brain drain on sending countries which is discussed by Commander et al. (2004), and Docquier et al. (2011). The positive effect on sending countries rises from the increasing investment on education due to higher returns to education, whereas the negative effect stems from the loss of human capital which is an advantage from the perspective of the receiving country (Docquier & Rapoport, 2011).

As a positive effect on source country, remittances are also discussed in the literature. It is shown that more educated immigrants tend to have higher probability to send remittances to their home country (Stark & Lucas, 1988; Brown & Poirine, 2005). However, Faini (2007) argues that effect of positive remittances is not enough to compensate the effect of brain drain.

Labor market impacts of skilled immigrants have been controversial in the literature in terms of the effects on native wages and entry wages of migrants. There are studies comparing the labor market outcomes of immigrants compared to natives and compared to other skill groups. Fix (2002) and Borjas (1996) claim that low-skilled immigrants have lower entry wages compared to higher skilled immigrants. Compared to natives, immigrants have lower wages and worse labor market outcomes as well (Antecol, Cobb-Clark, & Trejo, 2003; Causa & Jean, 2007). However, this difference is due to skill difference between migrants and natives. Borjas (1999) estimates the difference between wages of natives and immigrants after adjusting for the differences in educational attainment and finds out that the difference is much smaller. Borjas (1985) and Lubotsky (2007) look at different points in time and find that the wage difference between natives and immigrants are decreasing through time, though entry wages of immigrants are declining as well. This result is confirmed by Baker (1994), Bloom et al. (1994) and Grant (1999) for the U.S., Aydemir (2002), Aydemir & Skuterud (Aydemir & Skuterud, 2005) and Green et al.(2004) for Canada. When immigration of low-skilled labor is high, it decreases the wages of both existing low-skilled migrants and low-skilled natives (Jaeger, 1996; Borjas, Freeman, Katz, DiNardo, & Abowd, 1997). On the other hand, it increases the wages of both high-skilled existing immigrants and natives (Jaeger, 1996). Martin and Papademetriou et al. (1996) shows that high skilled immigration is detrimental to host country skilled labor in terms of wages. However, Borjas et al. (1997) shows that high skilled immigrants have a small impact on native wages. Contradicting the first result, Batalova (2006) also concludes that the high presence of immigrants in skilled jobs does not have an impact on native earnings.

Two different determinants of immigrant skills are mentioned in the literature. Chiswick (1999) and Grogger and Hanson (2011) argue that the returns to skills across host countries is the major factor. They claim that as the difference between the returns to skill increases between home country and host country, more educated people would migrate. Another determinant is the role of admission classes. Greenwood et al. (1991) and Cobb-Clark (1993) are first in the literature drawing importance to role of the immigration policies in shaping the labor market outcome of the immigrants.

It is claimed that immigration policies have impacts on outcomes discussed above and and especially they are important in determining the economic impacts of skilled migration (Aydemir, 2012). Moreover, Batalova (2006) points out the urgency of shaping immigration policies due to increasing competition for skilled immigrants among major receiving countries.

2.2 Immigration Policies

As mentioned above, immigration policies have an influence on skill distribution of immigrants. This section discusses the immigration policies of major immigrant receiving countries; Canada and the U.S.

Before 1960s, while immigration policies in the United States were guided by national quotas, Canada admitted immigrants only from a very few number of countries (Borjas, 1993; Boyd, 1976).

During early 60s both the United States and Canada undergone major policy changes. With the Immigration and Nationality Act of 1965, the United States abolished national origins quota system and implemented the preference system (Keely, 1971). Preference system made family unification the cornerstone of the immigration policy since 1965. The preference system allocated 70% of the visas for family reunification and 20% based on skills and 10% based on humanitarian grounds (Duleep & Regets, 1995; Borjas, 1993). Under the new system, the United States regulated the manpower aspect of the new immigration policy by introducing labor certification which ensured that immigrants with skills that are needed in the U.S. labor market were admitted (Keely, 1971; Boyd, 1976). During the same period in 1962 and 1967, Canada adopted changes in the immigration policies as well. Similar to the U.S., the new regulations implemented in 1962 removed the national origin quotas and emphasized family reunification (Borjas, 1993; Boyd, 1976; Beach, Green, & Worswick, 2007). In 1967, a new policy called the point system was implemented in Canada which emphasized manpower aspect of immigration (Troper, 1992; A. G. Green & Green, 1995). Under the points system, applicants are assesed based on a points test measuring age, education level, work experience, intended occupation and language ability (Constant & Zimmermann, 2013). Applicants must achieve a minimum number of points required. While both the U.S. and Canada emphasized manpower aspect of immigration in late 1960s, for the U.S. it was used as a gate-keeping tool rather than skill screening. For Canada the emphasis on skills were more observable (Borjas, 1993; Boyd, 1976; Beach et al., 2007). During 1990s with the enactment of Immigration Act of 1990 in the U.S., skilled immigration gained more importance (Batalova, 2006). The new regulations increased both the number of legal immigrants and number of immigrants admitted under employment visa category (Martin, Chen, & Madamba, 2000; Beach et al., 2007; Batalova, 2006).

2.3 Policy Effectiveness and Skill Differentials

The policy changes discussed above during 1960s had severe implications for the national origin distribution of the immigrants. First of all, there has been an inflow of non-Europeans to North America (Keely, 1971; Boyd, 1976). Immigrants from Asia, Oceania, Africa increased but the increase for Asia was very sharp for both Canada and the U.S. (Keely, 1971; Boyd, 1976). The policy changes also affected the occupational distributions of the immigrants. For the U.S., the major shifts were in the professional and household worker categories. Professionals increased due to Asian immigrant influx and households increased due to labor certification allocated for this category (Keely, 1971). While in the U.S. number for clerical and sales occupations decreased, it increased in Canada; the opposite happened for the professional and technical occupations (Keely, 1971; Boyd, 1976). Managerial occupations increased in both countries (Boyd, 1976). Due to points system Canada started receiving more educated immigrants with higher entry wages due to skill filtering (Borjas, 1993).

While it is shown that immigration policies aim to shape labor market outcomes, it is also important to know whether immigration policies discussed above achieved their goal. Bhagwati (2003), Castles (2004) claim that immigration policies cannot reach their goal of regulating immigration but rather change the way people migrate. Beine et al. (2011) focuses on the diaspora effect. They claim that effectiveness of the immigration policies decreases unless family reunification programs are revisited and reformed. On the other hand, Mayda (2010) and Ortega & Perri (2013) show that policies effect the magnitude and composition of immigrant flows.

The effectiveness of immigration policies are measured in terms of skilled immigrants they attract and their labor market outcome. Duleep and Regets (1992) compare immigrants arriving to Canada and the U.S. from same country of origins, Europe and Asia. They find that compared to the U.S. immigrants arriving to Canada are younger and more proficient in terms of language. Points system introduced by Canada was shown to be effective in reducing the age of arrival and increasing language proficiency. However, in terms of education and earnings immigrants were similar. Therefore, they conclude that points system fails to achieve its goal. On the contrary, Borjas (1993) extends this analysis by comparing immigrant skills of the U.S. and Canada from all country of origins rather than focusing only on Asia and Europe. His analysis shows that after the introduction of the points system Canada attracted more educated immigrants by altering the country of origin distribution of immigrants. Green and Green (1995) also shows that points system shifted the immigrant inflow to a more skilled inflow.

Aydemir (2002) mentions the importance of labor market outcomes of different visa categories for policy implementation. Aydemir (2002) analyzes different visa categories in Canada and finds out that the modest earnings advantage of skilled-workers do not translate into an earnings advantage in employment rates in the short-term. Cobb-Clark (2000) makes the same analysis for Australia and concludes that employment based immigrants have better labor market outcomes but family based immigrants adjust fast and the difference declines. Sweetman & Warman (2012) compare the labor market outcomes of different visa categories in Canada and find that each point assesed by the point system increase earnings by 2% and increases probability of being employed by 0.5%. Green and Green (1995), analyze the effectiveness of points system by comparing different visa categories in the Canadian system and show that the policy was effective in changing the composition of immigrants after it was introduced but the effect diminished once the policy was settled. De Silva (1997) compares different visa categories as well. In addition to Green and Green (1995), he compares visa categories for different cohorts and finds that for different cohorts earnings of different visa categories converge to each other with the time spent in the host country. He also points out the importance of country of origin. He finds that within skilled immigrants European immigrants are much more skilled.

The literature has focused on the importance of attracting skilled migrants, the effects of skilled migrants on the labor market, and the role of immigration policies in attracting skilled migrants. The literature also compares different visa categories as a measure of effectiveness of different immigration policies. While the skill differences between visa categories has been examined by several papers, the channels through which skill differential among immigrants is caused has not yet attracted much attention. Aydemir (2012) analyzes the skill differential for Canada and shows that skilled immigrants have higher skills compared to other visa categories due to points system generating higher skilled immigrants within a country of origin rather than across country of origins. Aside, high skilled immigrants increase the skill level by bringing higher skilled immigrants. For the U.S., Barrett (1998) examines the relative skill levels of immigrants admitted under different visa categories and he concludes that family based and skilled based immigrants differ in terms of their skills and the skill differential varies across country of origins. Therefore, the effect of a shift in a visa category would effect the skill level differently depending on the country of origin composition. Jasso and Rosensweig (1995) compare the occupational distribution of immigrants differing in their visa categories. Adjusting for the differences in age and country of origin, they find that employment based immigrants have higher skill level compared to adjusting marital immigrants.

For the first time in the literature, this study focuses on the skill differential between employment and family visa categories across different arrival cohorts in the U.S. The study further extends the analysis by focusing on the determinants of skilled migration and their efficacy in shaping the skill composition of immigrants.

3 DATA

The study uses INS data which contains information on immigrant demographics as the main source. U.S. Censuses and International Censuses are used to extract information on educational attainments of immigrants. The study combines INS data and other two data sets to get a skill measure for immigrants.

3.1 Data on Immigrant Demographics

Immigration Naturalization Service (INS) data currently known as United States Citizenship and Immigration Services (USCIS) is a data set published by United States Department of Justice containing information on the characteristics of aliens who became permanent residents of the United States. The data collection includes two types of immigrants. The first category, New Arrivals, arrived from outside the United States with valid immigrant visas issued by the United States Department of State. Those in the second category, Adjustments, were already in the United States with temporary status and were adjusted to legal permanent residence through petition to the United States Immigration and Naturalization Service. Variables include port of entry, month and year of admission, class of admission, and state and area to which immigrants were admitted. Demographic information such as age, sex, marital status, occupation, country of birth, country of last permanent residence, and nationality is also provided. The data set contains information for each year since 1974 to 2000. Each year includes data for aliens who became legal permanent residents of the United States in that fiscal year starting from October of the previous year through September of that year. The data set excludes the aliens who are granted permanent residency under the Immigration Reform and Control Act of 1986.

This study uses the variables; class of admission and several demographic variables such as country of birth, occupation, age and sex.

Based on different admission subcategories that is reported, the study classifies class of admission types into 9, based on the USCIS definitions. According to the preference system, the channels to immigrate to the U.S. is based on either a family relationship with a U.S. citizen or a legal permanent resident or on employment skills. In this study, first type which is based on family ties is divided into two: Family Preference Immigrant Visas and Immediate Relative Immigrant Visas. Family Preference Immigrant Visas are allocated for spouses, minor children and unmarried sons or daughters of lawful permanent residents (LPRs). Moreover, they are also allocated for more distant relatives of US citizens such as married sons or daughters, brothers and sisters. Immediate Relative Immigrant Visas are allocated for close relatives of US citizens such as spouse, minor children and parents. Second type class of admission is based on employment preferences. This visa category includes Priority Workers, Professionals Holding Advanced Degrees and Persons of Exceptional Ability, Certain Special Immigrants and Immigrant Investors. Families of these immigrants are also included in Employment Preference Immigrant Visa. Employment is first divided into two categories depending on the skill of the immigrant; employment preference and employment preference by demand. Employment preference is further divided into two; major applicants and their families are separated into different classes and in total there are 4 subcategories under employment preference. Another category is for refugees and asylum seekers. Moreover, Diversity visa category is included starting from 1995.

Throughout the analysis, two of these visa categories will be used; family preference immigrant visas which will be referred as family visa category and employment preference visa category excluding both employment by demand and families which will be referred as employment visa category.

The country of birth variable includes approximately 150 different countries for each year. Due to sample size concerns, the analysis is done at regional level rather than country based. Therefore, the data is combined into regions by aggregating different countries into regions based on the United Nation's regional classification [1]. There are 6 major regions that is of our interest: Europe, Asia, Africa, Oceania, North America, South America. In some of the analysis Mexico is excluded from South America and treated as a separate

[1] http://millenniumindicators.un.org/unsd/methods/m49/m49regin.htm

group. In some of the tables and outputs, Oceania and Africa will be excluded due to small observation size.

Another major variable of interest is occupation. The occupation variable reports the employment that will be performed by the immigrant in the United States if the immigrant is admitted under the employment preference visa category. Otherwise, Immigrants admitted in other categories report their occupation in either the home country or in the U.S. depending on whether they newly arrived or adjusted. Immigrants who are already present and are in the U.S. report their current occupation in the U.S., and immigrants newly arriving in the U.S. report their occupation in their home country. Even though, some of these immigrants may not work in their reported occupation in the U.S., occupation serves as proxy for skill level and thus is important. The occupation variable contains 25 different occupational categories. Moreover there are categories for students, housewives, children, unemployed/retired or immigrants who are not in the labor force these categories which excluded from the analysis. The number of occupational categories change from year to year. The minimum number of occupation types is contained in 1983. Therefore, all of the other years are recoded to be consistent with occupational code of 1983. The INS data for 1983 has 23 occupational types and other excluded categories. The age variable reports ages of each immigrant which enables us to focus on the working age. Since the primary focus is to derive a skill measure using occupation variable, only the working population is taken into account and aliens below age 22 and above age 65 is excluded from the analysis. The study also uses sex variable to examine the differences between male and female. There are some unreported or unknown observations which are excluded throughout the analysis.

3.2 Data on Skill Measure

Educational attainment is used as a skill measure of immigrants. Since there is no information on education in INS data two different data sets, US Censuses and International Censuses are used to extract the years of schooling levels of immigrants. Census data sets are extracted from Integrated Public Use Micro-data Series (IPUMS) Minnesota Population

Center (King, 2010).

Years of schooling variable is drawn using U.S. Censuses for 1980, 1990 and 2000. Census data includes variables on birth place, census year, year of immigration, age, sex, and detailed occupation level that is of our interest in the analysis. Census data contains information on whole U.S. population. Using the birth place variable the sample is restricted to only immigrants by dropping the individuals born in the United States. Since the analysis is regional rather then on country level, a region variable is generated using birth place variable. Regions used for Census data is the same as we used in the INS data to keep the variables consistent. Occupation variable is recoded so that the occupational codes refer to the same occupations as in INS data. Year variable refers the census year. Subtracting the year of immigration from the year we get how many years have passed since the individual arrived to the U.S. Adding his age on top of this difference we get the age of the individual at the time of the census year. A new age at arrival variable is generated based on the method described above. This new variable is used to restrict the sample to the working age same as it is restricted in the INS data which is between 22 and 65. Using the sex variable differences between male and female can be identified. Detailed education variable is used as a measure for years of schooling. Detailed education variable includes 25 different categories starting from no school completed to 8+ years of college. For each of these categories a number of years of schooling completed is assigned and a new "years of schooling"variable is generated.

Second method used to derive years of schooling information of immigrants is using the Census data of immigrant's home countries. Ipums International (2013) gathers Census data sets of 74 countries from different regions. This study extracts the most recent censuses for each of the country existing in the INS data. Combining all of these censuses together, the data set includes variables; census year, country of origin, birth year, age, sex, internationally recoded detailed education, and internationally recoded occupation. Similar procedures with the U.S. Censuses is applied. The data set consists of 74 countries but 4 of them does not have information on occupation and 2 of them does not have information on education. Using the country variable a region variable is generated to be used in the matching procedure. Using the age variable the data set is restricted to working age population above 22. Censuses are gathered from different countries in different years therefore a birth cohort variable is generated to reach a similar birth cohort with INS data. Using the sex variable the analysis is carried both for males and females. The occupation variable consists of 8 different categories which are more general forms of occupation categories discussed in the INS data. Detailed education variable is used as a measure for years of schooling in the same way as explained for the U.S. Censuses.

3.3 Merging Procedure

To analyze the skill differences between different visa categories, we need educational levels of each individuals under different categories. Information on individuals under different visa categories will be taken from INS data and information on educational attainment will be taken both from the U.S. and International Census data sets discussed above. This section discusses how INS data set is combined with two other data sets to get educational information on immigrants.

The first data set is acquired using U.S. Censuses for years 1980, 1990, and 2000. For each of the Census year, years of schooling variable is collapsed by occupation, sex and region so that we estimate the average schooling level for different occupations in different regions for both males and females. This process is repeated for 3 censuses because for different arrival cohorts, years of schooling levels of immigrants from different regions and different occupations might change. In order to match the Census Data with the INS data, we have consistent variables for occupation, region, sex for both data sets. Knowing the average years of schooling for each individual using Census data, we combine it with the INS data based on occupation, region and gender. INS data between 1974 to 1984 is matched with 1980 Census. Data starting from 1984 to 1994 is matched with 1990 Census. The rest is matched with 2000 Census. This data set will be referred as the ”first data set” that will be used in our analysis.

To confirm the results achieved by using the first data set, a second data set is generated by matching INS data with International Censuses. Years of schooling variable of International Census data is first collapsed by cohort, country, occupation and sex. Secondly, it is collapsed by region as well. Collapsed data is matched with the consistently generated INS data. For common countries of both data sets, the merging procedure is done at the country level otherwise regionally collapsed data is used. This data set will be referred as the ”second data set” that will be used in our analysis.

The first and the second data sets are both used to match INS data with years of schooling information. However, their sources of information is different. The first data set uses U.S. Censuses focusing on information on immigrants for three different time periods and the years of schooling information is therefore at the regional level. On the other hand, the second data set uses International Censuses gathered for different countries and different birth cohorts, and uses this information for years of schooling. Therefore, using two different data sets through the analysis will help to strengthen our results on skill levels.

4 DESCRIPTIVE STATISTICS

This chapter provides brief information about number of immigrants and skill level across major regions and major visa categories that will be used throughout the analysis. The comparisons will be made for both of the data sets used in the merging procedure[2]

4.1 Number of Immigrants

Figure 1 presents the number of total immigrants over time. The number of immigrants follow an increasing trend. Number of immigrants from each region through time is presented by Figure 2. For each year, majority of the immigrants are from Asia which is followed by Europe, South America and Mexico. Starting from 1990, there is a sharp increase in the number of immigrants from all of the regions with an exception of South America, especially for Asia and Europe, with a decline starting in 1996. Figure 3 presents the number of immigrants under different visa categories. As the figure presents, the U.S. is accepting more immigrants from family visa category rather than employment visa category. Looking at the trend over time, number of immigrants under family visa category is increasing whereas for employment visa category the increase is only observed starting from 1990s.

When we consider the within regional composition of visa categories, Figure 4 presents the number of immigrants under different visa categories for Europe. It is observed that between 1980 and 1992, the number of immigrants under family visa category follows an increasing trend for Europe, whereas employment visa category stays stable until 1990s. With a sharp increase of employment visa category starting from 1990s, the number of immigrants under family visa category declines sharply. Figure 5 for Asia shows that the pattern for employment visa category is similar, while family visa category is following a

[2]The years of schooling mentioned through the section is for the first merging procedure, the second merging procedure follows the first with a 2 year difference for most of the analysis. It will be mentioned if otherwise is observed.

much smoother pattern. For Mexico in Figure 6, admission under employment visa category has always been low with an exception for 1988, whereas, starting from 1984 number of immigrants under family visa category increases.

In addition to the discussion of visa category's share within regions, it is important to draw attention to regional distributions of visa categories as well. Figure 7 presents the number of immigrants under family visa category from different regions. From the figure it is observed that immigrants from Asia is higher compared to other regions for all years. The number of immigrants from Asia under family visa category is almost stable across years excluding some extreme values, whereas for Europe between 1979 and 1990 it follows an increasing trend and for Mexico this number follows an increasing trend for all years. Figure 8 for employment visa category shows that the number of immigrants from Mexico is stable over time. For Europe, this number is stable until 1990s increases after this period. For Asia, the number for employment visa category is increasing over time. Starting with 1990s, the number of employment visa category for both Asia and Europe increases very sharply from 1000-2000 up to 22000-23000.

4.2 Skill Comparisons

Figures 9 and 10 present the mean years of schooling of immigrants from each region over time for both data sets. (U.S. Censuses and International Censuses). Both of these figures have a similar pattern. Table 1 shows that Europe and Asia have the highest skill level with 13.7 and 14 years of schooling on average respectivel and Mexico is the least skilled group with 8 years of schooling on average. Skill levels follow a stable pattern for Asia and South America whereas skill level in Europe and Mexico increases especially after 1990s which is sharper in Figure 10.

Figures 11 and 12 present the mean years of schooling for different visa categories over time for two merging procedures separately. From Table 2 it is observed that immigrants arriving through employment visa category is more skilled with 14.1 years of schooling compared to 12.9 years for family visa category on average. Immigrants arriving through employment visa category are less skilled compared to immigrants arriving through family visa category until 1976. Between 1976 and 1984, employment visa category is more skilled [3]. After 1984 and up to 1990 immigrants under employment visa category and family visa category have similar skill levels with a sharp increase afterwards for immigrants under employment visa category. The patterns are almost the same for both merging procedures with a two year difference in level of years of schooling.

Distribution of skill level is not stable within regions. Figures 13 and 14 presents the skill levels of visa categories for Europe and Figures 15 and 16 presents the same for Asia. For family visa category, average years of schooling od Asia and Europe follow opposite trends; while the average years of schooling of Europe is increasing it is decreasing for Asia. For employment visa category, the skill level for Europe increases until 1980 and increases afterwards. For Asia, the skill level is higher between periods 1976-1984 and 1989-1997.

Comparing the skill levels across regions for a given visa category, Figures 17 and 18 show that under family visa category the skill level for Europe increases through time and decreases for South America and Asia. Figures 19 and 20 show that under employment visa category, the skill level for all regions increases starting in 1990s.

From the discussions above, it is important to point out that the skill level of family visa category is stable over time since mid 1970‘s which is presented in Figures 11 and 12. From the same figures it is observed that skill level of employment visa category is similar or higher than family visa category across time. This is crucial in analyzing the effectiveness of policies since policies are expected to effect the employment visa category. It can be observed that a change in skill levels is reflected by a change in employment visa category. The increase in employment visa category is due to Europe and Asia while the number for Mexico stays the same. To confirm these results, the following chapter analyzes the skill difference and its components.

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[3] There is not enough observation to comment on the skill level of immigrants arrived in 1978 and 1979 under employment visa category.

5 DETERMINANTS OF SKILL DIFFERENTIALS

This section aims to understand the factors behind the skill differences among immigrants arriving through different channels over time. The major differences in terms of selection process in the U.S. is between family visa category and employment visa category as discussed in Section 3.1. The skill difference between family visa category and employment visa category is presented in Figure 11 and Figure 12. The rest of the study examines the difference presented in these figures.

The skill level might change in two ways. It is possible that the U.S. may choose higher educated, more skilled immigrants in a given region. The alternative mechanism, without changing the selection criteria, is to increase the share of immigrants from high skilled regions. Hence, skill distribution can be affected by changing the selectivity or by changing the regional composition of immigrants. More skilled immigrant distribution is achieved if policies increase the share of skilled immigrants or within employment class immigrants from better occupational background is selected. These two effects account for selectivity which attracts more skilled immigrants within regions. Whereas, it is possible to increase the overall skill level by changing the regional composition of the immigrants in a way that more immigrants arrive from higher educated regions. This effect attracts more skilled immigrants across regions.

First, we want to understand how the selectivity has changed. To this end, we use simple Ordinary Least Squares method. Regressions analysis identifies the effects of region, visa categories and year of arrival on years of schooling. Second, we want to determine what is the major component of the skill change. In order to identify this, Oaxaca decomposition method is used. By comparing family visa category and employment visa category, we measure the effect of regional composition change and selectivity change and examine which is more effective in the U.S. over time.

The main regions that will be discussed throughout the chapter are Europe, Asia, and Mexico since the U.S. receives most immigrants from Asia and Europe. In addition, Mexican immigrants play a major role in the U.S. immigration policies as discussed in Section 2. The analysis for other regions can be found in the Appendix.

5.1 Regression Analysis

The analysis starts by discussing the effects of different years, regions, and visa categories on average years of schooling. The analysis continues with controlling for the effects of visa categories and regional effects to capture the main reason behind the skill change. The effects of different visa categories measure the selectivity of immigrants and may change over time due to possible policy changes or occupational composition changes. To capture the changes in selectivity over time, last section discusses the interacted regressions which interacts visa categories with years. Simple Ordinary Least Squares (OLS) estimation will be used throughout the regression analysis.

Our first model, yearsofsch=α+β_1*year, in Table 3 -Regression (1) shows the change in average years of schooling across time. Results shows no clear time trend. For time periods 1975-1980, 1984-1985 and after 1990 the skill level has increased while in other periods it is similar with base period, 1974. It is observed that there is a significant increase in the skill levels of immigrants after 1990, whereas in other periods the average years of schooling is similar to the base year, 1974. The rise in skill level after 1990s is expected since there is a major policy change in 1990. However, this increase may be driven by the changes in regional composition of immigrants. In order to capture this effect Table 3 -Regression (2) controls for regions, yearsofsch=α+β_1*year+β_2*region. It is expected that for years where more immigrants from lower educated countries are selected the coefficients in Regression (1) would be higher, whereas, when more immigrants from higher educated regions are selected then the coefficients would be lower. Comparing the coefficients of Table 3- Regressions (1) and (2), it can be observed that the breaks in year coefficients disappear and all of the coefficients turn to positive. This result tells us that in years where average skills are lower than the base year, this is mainly due to a higher share of immigrants admitted from lower educated source countries. Low number of immigrants from Asia and Europe in 1979 might be the reason behind the increase in the coefficients of those years (Figure 2) since Europe and Asia have higher years of schooling on average (Figure 9). The increases in the coefficients of 1986 to 1989 is possibly due to the high number of immigrants from Mexico while the others are stable. In 1990s after controlling for region of origin, there is still a major increase in skill level. Above analysis ignore the visa distribution of immigrants. However, the effect of admission from a region with higher mean years of schooling would seem lower if the U.S. would not accept immigrants under employment visa category. Hence, to capture the selectivity, a control for visa categories is added. Table 3 -Regression (3) controls for visa categories, yearsofsch=α+β_1*year+β_2*region+β_3*visacategory. It is expected that, if more immigrants are accepted under employment visa category in a given year we would expect the coefficients of corresponding year dummy in Regression (1) to be lower compared to the coefficients of Regression (3). Comparing the coefficients of Table 3- Regressions (1) and (3), the increase in coefficients of 1979-1983 might be due to the high level of family visa category and the decrease in the coefficients for periods 1984-1985- and 1990-1994 is possibly due to lower number of immigrants under family visa category compared to other years and higher number of immigrants under employment visa category (Figure 3). Also in this model 1990s has significant effect.

The second model reported in Table 4 focuses on the skill differentials across regions. For this purpose, we estimate the differences in mean years of schooling across regions, yearsofsch=α+β_1*region in Table 4- Regression (1). On average, mean years of schooling is higher for immigrants originated from Europe (1.region) and Asia (2.region) compared to North America (base category) ,whereas, mean years of schooling for immigrants from Mexico (7.region) and South America (6.region) is lower compared to North America (base category). To capture the effects of admission under different visa categories visa category dummies are added, yearsofsch=α+γ_1*region+γ_2*visacategory. Controlling for visa category Table 4- Regression (2) reports that, while the coefficients for Europe and Asia decreases, coefficients for South America and Mexico increases since more immigrants from

Europe and Asia come under employment visa category which accounts for higher skill level (Figure 3). Regional selection is also expected to be effected from time which is taken into account in Table 4- Regression (3), yearsofsch=α+γ_1*region+γ_2*visacategory+γ_3*year. For Europe and Asia, the coefficient decreases since for both regions skill levels increase significantly in early 1990s (Figures 13 and 15).

The third model reported in Table 5 focuses on the skill differentials across visa categories. Table 5- Regression (1) presents the results for average differences in mean years of schooling across visa categories, yearsofsch=α+θ_1*visacategory. Compared to Refugees (base category), immigrants arriving through family visa category (1.visacategory) and employment visa category (2.visacategory) are more educated by 0.24 and 1.38 years of schooling, respectively. Moreover, Suspecting that specific regions might be favored in the selection process regional dummies are added in Table 5- Regression (2), yearsofsch=α+θ_1*visacategory+θ_2*region. It is observed that, the coefficient for family visa category increases while coefficient for employment visa category stays the same suggesting that education levels of immigrants under family visa category would be higher would be higher if the region of origin composition was the same with employment visa category.

Table 5- Regression (2) examines the differences in skill levels for different visa categories controlling for year and region. These regressions assume that the effect of visa category is constant over time. However, selectivity of immigrants which is captured by the coefficients of visa category may change over time. To allow for this possibility, visa category dummies are interacted with year and additionally regional dummies are added to capture both the regional effects and selectivity over time. Using these parameter estimates adjusted coefficients are generated so that the comparison of the numbers are easier. For family visa category, the adjusted coefficients are calculated by adding family visa category coefficient, each year's coefficient, and that year's interacted term with the family visa category (1.visacategory). Same procedure is applied for employment visa category.Table 6 presents the adjusted coefficients of the interacted regression. Table 6 suggests that, with

the exception of years 1975, 1976, and 1979; the selectivity for family visa category does not change over time. Whereas, for employment visa category for periods 1980-1982 and 1990-1998 the selectivity of employment visa category is higher compared to other years.

U.S. immigration policy states that visa categories do not have any constraints on regions. Therefore, it is assumed that regional effect does not change over time. However, to measure the effectiveness of selectivity in each region the interacted regression is re-estimated for regional sub-samples. Due to lack of observations, some effects cannot be measured for Mexico. Table 7 presents the adjusted coefficients for each region. Focusing on the family visa category coefficients of each region, it is observed that for Europe and Asia follows a stable pattern. However, for Mexico there is a sharp increase in 1984.

Overall the regression outputs suggest that changing regional composition of immigrants affects only family visa category, which is mostly due to the changes in the share of immigrants from Mexico. Moreover, the selectivity change is reflected in employment visa category which is mostly affected by Europe and Asia.

5.2 Oaxaca Decomposition

Figures 11 and 12 present the skill levels of family visa category and employment visa category. From both graphs, it can be observed that unlike skill level of family preference, skill level of employment visa category changes over time. Section 5.1 confirms this result by concluding that selectivity does not affect the family visa category but affects employment visa category. This section focuses on the skill difference between these visa categories and identifies the causes behind this difference. The analysis is done for both data sets described in Section 3.3.

The analysis is built upon the analysis done by Aydemir (2012) where he analyzes the skill differential between two visa categories based on family ties and employment for Canada. This analysis differ from Aydemir (2012) in terms of adding a time component.

The specifications of the model is as follows: for each region of origin group j, the mean years of schooling is defined to be S_{ijt} for each visa category i and year t. The mean years of schooling for visa category i is calculated by taking a weighted average of S_{ijt} over N region of origin groups and T years such that $S_i = \sum_{t=1}^{T}\sum_{j=1}^{N} p_{ijt}S_{ijt}$ where p_{ijt} is the fraction of immigrants from region of origin group j and visa category i for year t in total number of immigrants. Let S_e and S_f represent the average years of schooling of immigrants arriving through employment visa category and family visa category, respectively. Moreover, χ_e and χ_f are $1 \times N$ vectors representing the source region distributions in each visa category. β_f is a $N \times 1$ coefficient vector where each row measures the mean years of schooling of each region among family visa category and β_e is a $N \times 1$ coefficient vector where each row measures the mean years of schooling of each region among employment visa category. The specifications for S_e and S_f above represent the overall skill levels. Besides the overall difference, the skill levels can be defined on a yearly basis as well. For this purpose, the mean years of schooling is calculated by taking a weighted average of S_{ijt} over N region of origin groups for each year separately such that $S_{it} = \sum_{j=1}^{N} r_{ijt}S_{ijt}, \forall t$ where r_{ijt} is the fraction of immigrants from region of origin group j and visa category i for year t in year t. The other specifications are same but measured for each year separately.

The differences in mean years of schooling between family visa category and employment visa category (S_e - S_f) are analyzed using Blinder-Oaxaca decomposition (1973) approach:

$$S_e - S_f = (\chi_e - \chi_f)\beta_f + \chi_f(\beta_e - \beta_f) + (\chi_e - \chi_f)(\beta_e - \beta_f) \tag{1}$$

$$S_{et} - S_{ft} = (\chi_{et} - \chi_{ft})\beta_{ft} + \chi_{ft}(\beta_{et} - \beta_{ft}) + (\chi_{et} - \chi_{ft})(\beta_{et} - \beta_{ft}) \quad , \forall t \tag{2}$$

The left hand side of Equation 1 refers to overall difference in mean years of schooling between family visa category and employment visa category. The left hand side of Equation 2 refers to the yearly difference in mean years of schooling. The first component on the right hand sides of both equations are the endowment effects which measures the part of the differential that is due to group differences. In the context of this analysis, the group variables are χ_e and χ_f measuring the regional composition of visa categories. Endowment effect reflects the change in mean years of schooling of family visa category if they have the same regional composition as employment visa category. The endowments effect will be referred as "across differential" from now on since it measures the change in skill levels if there is change across regions keeping the selectivity of visa categories constant. The second components are coefficients effect which measures the contribution of the coefficients to the difference. In our context, these coefficients are β_e and β_f referring to the selectivity of each visa category. This component reflects the change in years of schooling if the selectivity of family visa category is the same as employment visa category. Coefficients effect will be referred as "within differential" since it measures the change in skill levels if there is a better selection within region of origin groups keeping region of origin composition constant. The third term is the interaction effect measuring the simultaneous effect of differences in the endowment and coefficient effects.

5.2.1 Restrictions

This methodology was implemented using the Oaxaca STATA command by (Jann, 2008). All of the decompositions are default three-fold decompositions. The analysis uses regional dummies as control variables. As it is mentioned in Oaxaca and Ransom (1999), the contributions of dummy variables representing a categorical variable to the differential depends on the choice of the omitted dummy category. Using Gardeazabal and Ugidos (2004) and Yun (2005) alternative approach this problem is avoided. Their approach imposes a restriction on the coefficients of the dummy variables, so that they all sum to zero which can be interpreted as estimating the effect of each dummy category as a deviation from the grand mean (Jann, 2008). Using this method, we can estimate the contribution of each dummy category to the differential which is invariant to the choice of base category. Using "categorical" specification the dummy variables (regions) are identified.

We are not only interested in the total effect of changing regional composition but also the contributions of each region one by one. For this, the “detailed” specification is added to evaluate the detailed contributions of each region. The ‘detailed” specification has two problems in interpretation. First, categorical variables do no have a natural zero which is solved by using “categorical” specification. The second problem is and It is also important to note that throughout the analysis the reference group is family visa category. That is, for calculating the within and across differential the differences are weighted by the coefficients of family visa category.

5.2.2 Decomposition Results

The decomposition outputs in Tables 8 and 10 report the mean predictions by groups and their differences in the first panel. In the second panel, the difference is decomposed into three parts as mentioned above: endowments, coefficients, and interactions.

Table 8 reports the results for the first sample where we take all of the individuals irrespective of the year, the mean years of schooling is reported to be 14.05 for employment visa category and 12.93 for family visa category, yielding a years of schooling difference of 1.12. 64% of this total difference is explained by the change in selectivity and 27% is explained by regional composition change. The coefficient of Endowments in Table 8 reflects that if regional composition of family visa category is same as employment visa category, their years of schooling would be 0.31 years higher. Moreover, if immigrants under family visa category were selected as employment preference immigrants keeping their region of origin composition constant their years of schooling would be 0.72 years higher. Therefore, in overall it can be concluded that employment visa category generates a higher skilled immigrant flow mainly by selecting more skilled immigrants from the regions rather than changing the region of origin composition. Within differential is the major factor generating skill difference.

Table 9 analyzes the components of endowments and coefficients effects by region. From Table 9, it is observed that across differential is mostly due to Mexico. Therefore, skill distribution can mostly be affected by changing the proportion of Mexico in total distribution. The endowment coefficient of Mexico tells us that if the proportion of Mexico in the distribution of family visa category were to be the same proportion in the distribution of employment visa category than the family preference immigrants would be 0.18 years more educated on average.

The analysis is further extended for each year to understand how across differential and within differential behaves over time. Tables 12 and 13 report the oaxaca coefficients from oaxaca decomposition analysis for each year. It is observed that, whenever the across differential (endowment coefficient) is higher, immigrants under family visa category is more educated on average. Whereas, when within differential is higher skill level of employment visa category is higher. Looking at these numbers on a graph, from Figures 25 and 26 it is observed that it is mostly the within differential causing the skill difference while across differential is following a smoother line.

5.2.3 Discussion of Results

Selectivity is determined by either policy changes or other factors effecting the home country selection such as a change in educational system or economic factors. Figures 11 and 12 point out that skill level of family visa category is following a smooth line. Years of schooling of the immigrants under family visa category does not change as much as employment visa category. If family visa category also were to be affected from a policy change this should be reflected in the figures by an increase or decrease in the skill level. Moreover, if compulsory education were to change then it should have affected immigrants arriving through both channels. However, selectivity affects only the employment visa category. Analyses of the skill differential using regression analysis and oaxaca decomposition, indicates that observed changes in skill levels are driven by policy changes.

6 CONCLUSIONS

This study analyzes the skill level of immigrants arriving to the U.S. over the time period 1974-1998. Analyzing the skill levels, the main focus is on different region of origins and different visa categories. Moreover, the study addresses the causes behind the skill difference among different visa categories.

There are numbers of novelties in this paper that has not been previously studied. First of all, the paper presents the skill distribution of immigrants to the U.S. over time depending on their region of origin, visa category and gender for the first time. The study finds that the skill level of family visa category is stable over time while the employment visa category is increasing after 1990s. This is the first conclusion confirming the effect of immigration policies in increasing the skill level. Secondly, using regression analysis it is shown that, over time the selectivity for family visa category does not change. However, the selectivity for employment visa category increases. This also confirms the effect of Immigration Act of 1990 since the increase is observed in the targeted visa category. Given the differences in skill levels, the factors behind these differences are also analyzed using Oaxaca Decompositions. The decomposition results suggest that the difference in the skill levels between employment and family visa category is primarily due to differences in selectivity of visa categories rather than differences in region of origin composition.

This study has major policy implications. It is shown that rather than selecting more skilled immigrants across countries by changing region of origin composition, it is more effective to select more skilled immigrants within region of origin groups by adjusting the selectivity.

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Appendices

A Tables

Region	Mean Years of Schooling using U.S. Censuses	Mean Years of Schooling using International Censuses
Europe	13.7	11.3
Asia	14.0	10.3
North America	12.4	10.6
Mexico	8.0	7.0

Table 1: Mean Years of Schooling for Different Regions

Visa Category	Mean Years of Schooling using U.S. Censuses	Mean Years of Schooling using International Censuses
Family	12.9	10.1
Employment	14.1	11.2
Refugee	12.7	9.5

Table 2: Mean Years of Schooling for Different Visa Categories

Table 3: Regressions controlling for Region and Visa Category

	(1)	(2)	(3)
	yearsofsch	yearsofsch	yearsofsch
1975.year	0.419***	0.513***	0.579***
	(31.43)	(47.59)	(54.06)
1976.year	0.486***	0.381***	0.381***
	(39.22)	(37.98)	(37.85)
1977.year	0.304***	0.346***	0.333***
	(26.40)	(37.01)	(35.76)

	(1)	(2)	(3)
	yearsofsch	yearsofsch	yearsofsch
1978.year	0.0491***	0.0731***	0.0816***
	(4.44)	(8.15)	(9.10)
1979.year	-0.212***	0.119***	0.117***
	(-16.57)	(11.47)	(11.28)
1980.year	0.0255*	0.216***	0.128***
	(2.14)	(22.42)	(13.38)
1981.year	-0.0979***	0.139***	0.0358***
	(-8.32)	(14.53)	(3.78)
1982.year	-0.0620***	0.103***	0.0414***
	(-5.51)	(11.33)	(4.53)
1983.year	-0.277***	0.0125	-0.0719***
	(-24.76)	(1.38)	(-7.90)
1984.year	0.337***	0.196***	0.00628
	(28.98)	(20.80)	(0.67)
1985.year	0.486***	0.292***	0.102***
	(41.90)	(31.12)	(10.82)
1986.year	-0.0988***	0.205***	0.0723***
	(-8.96)	(22.99)	(8.08)
1987.year	-0.149***	0.203***	0.0203*
	(-13.60)	(22.96)	(2.29)

	(1)	(2)	(3)
	yearsofsch	yearsofsch	yearsofsch
1988.year	-0.242***	0.155***	-0.0763***
	(-21.96)	(17.31)	(-8.51)
1989.year	-0.0929***	0.164***	-0.00872
	(-8.39)	(18.33)	(-0.97)
1990.year	0.510***	0.338***	0.137***
	(44.36)	(36.31)	(14.59)
1991.year	0.235***	0.119***	-0.0324***
	(20.75)	(13.05)	(-3.54)
1992.year	0.863***	0.644***	0.254***
	(79.29)	(73.02)	(28.63)
1993.year	0.656***	0.557***	0.320***
	(62.08)	(65.15)	(37.20)
1994.year	0.676***	0.797***	0.493***
	(62.50)	(91.03)	(56.23)
1995.year	0.760***	0.700***	0.396***
	(67.58)	(76.91)	(43.38)
1996.year	0.310***	0.453***	0.109***
	(29.01)	(52.37)	(12.49)
1997.year	0.217***	0.508***	0.183***
	(20.06)	(58.05)	(20.68)

	(1)	(2)	(3)
	yearsofsch	yearsofsch	yearsofsch
1998.year	0.475***	0.730***	0.503***
	(39.61)	(75.20)	(51.82)
1.region		1.269***	1.190***
		(353.42)	(331.25)
2.region		1.545***	1.448***
		(528.66)	(495.10)
6.region		-0.825***	-0.915***
		(-170.71)	(-189.72)
7.region		-4.391***	-4.446***
		(-998.28)	(-1003.81)
1.visacategory			0.557***
			(109.12)
2.visacategory			1.299***
			(203.50)
3.visacategory			0.361***
			(69.74)
7.visacategory			1.000***
			(165.88)
8.visacategory			0.0129
			(1.51)

	(1)	(2)	(3)
	yearsofsch	yearsofsch	yearsofsch
9.visacategory			-0.260***
			(-30.84)
_cons	12.58***	12.09***	11.80***
	(1420.65)	(1626.41)	(1373.82)
N	4270546	4270546	4270546

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Regressions controlling for Visa Category and Year

	(1)	(2)	(3)
	yearsofsch	yearsofsch	yearsofsch
1.region	1.320***	1.214***	1.190***
	(368.10)	(338.92)	(331.25)
2.region	1.558***	1.447***	1.448***
	(532.93)	(494.79)	(495.10)
6.region	-0.814***	-0.916***	-0.915***
	(-167.94)	(-189.63)	(-189.72)
7.region	-4.390***	-4.453***	-4.446***
	(-997.01)	(-1005.65)	(-1003.81)
1.visacategory		0.540***	0.557***
		(108.93)	(109.12)
2.visacategory		1.358***	1.299***

	(1) yearsofsch	(2) yearsofsch	(3) yearsofsch
		(221.59)	(203.50)
3.visacategory		0.355***	0.361***
		(69.74)	(69.74)
7.visacategory		1.029***	1.000***
		(177.80)	(165.88)
8.visacategory		0.0998***	0.0129
		(11.97)	(1.51)
9.visacategory		-0.263***	-0.260***
		(-31.97)	(-30.84)
Year Effects			YES
_cons	12.41***	11.95***	11.80***
	(5367.22)	(2513.52)	(1373.82)
N	4270546	4270546	4270546

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Regressions controlling for Region and Year

	(1) yearsofsch	(2) yearsofsch	(3) yearsofsch
1.visacategory	0.245***	0.540***	0.557***
	(40.58)	(108.93)	(109.12)
2.visacategory	1.383***	1.358***	1.299***

	(1)	(2)	(3)
	yearsofsch	yearsofsch	yearsofsch
	(185.41)	(221.59)	(203.50)
3.visacategory	-0.364***	0.355***	0.361***
	(-59.07)	(69.74)	(69.74)
7.visacategory	0.908***	1.029***	1.000***
	(128.51)	(177.80)	(165.88)
8.visacategory	0.0786***	0.0998***	0.0129
	(7.66)	(11.97)	(1.51)
9.visacategory	-0.117***	-0.263***	-0.260***
	(-11.55)	(-31.97)	(-30.84)
1.region		1.214***	1.190***
		(338.92)	(331.25)
2.region		1.447***	1.448***
		(494.79)	(495.10)
6.region		-0.916***	-0.915***
		(-189.63)	(-189.72)
7.region		-4.453***	-4.446***
		(-1005.65)	(-1003.81)
Year Effects			YES
_cons	12.62***	11.95***	11.80***
	(2249.10)	(2513.52)	(1373.82)

	(1)	(2)	(3)
	yearsofsch	yearsofsch	yearsofsch
N	4270546	4270546	4270546

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Family Visa Category	Employment Visa Category
1975	4.3	−0.6
1976	2.5	−0.5
1977	1.6	4.2
1978	1.6	−1.7
1979	2.6	−1.4
1980	1.4	4.6
1981	1.3	4.4
1982	1.4	4.0
1983	1.4	2.7
1984	1.0	0.2
1985	1.3	2.1
1986	1.7	1.4
1987	1.3	1.5
1988	0.3	0.7
1989	1.3	1.2
1990	1.8	1.1
1991	1.4	1.8
1992	1.3	2.5
1993	1.4	3.4
1994	1.7	3.1
1995	1.6	2.9
1996	1.5	2.4
1997	1.6	2.1
1998	1.7	4.0

Table 6: Interacted Regression Coefficients (Base Year 1974)

	Europe		Asia		Mexico	
	Family Visa Category	Employment Visa Category	Family Visa Category	Employment Visa Category	Family Visa Category	Employment Visa Category
1975	−0.5	−2.3	2.8	−0.7	–	–
1976	−0.8	−2.0	2.0	6.1	–	–
1977	−2.2	0.9	0.9	−0.6	2.9	3.7
1978	−1.4	−3.0	1.0	−1.1	2.8	–
1979	0.4	−2.1	1.2	3.4	2.8	3.0
1980	−2.2	2.7	0.3	3.0	2.5	3.7
1981	−2.0	2.6	0.1	2.8	2.6	–
1982	−1.3	0.9	0.2	0.7	2.6	5.8
1983	−1.1	−0.4	0.2	−1.7	2.6	–
1984	0.5	−0.5	−0.3	−0.6	5.0	4.3
1985	0.7	0.2	0.1	−0.8	4.3	3.8
1986	1.5	0.2	0.6	2.1	3.8	–
1987	0.5	1.1	−0.1	−0.8	3.6	3.7
1988	0.6	−0.2	−0.0	0.3	3.4	3.8
1989	0.2	0.1	−0.5	−0.0	3.6	3.5
1990	0.5	−0.2	0.1	4.1	3.9	3.6
1991	0.1	0.6	−0.3	−2.0	3.6	–
1992	0.1	0.9	−0.5	2.5	3.5	5.2
1993	0.5	1.8	−0.3	0.6	3.5	4.8
1994	1.1	1.3	0.1	1.4	3.5	4.9
1995	0.9	1.9	−0.1	4.0	3.5	–
1996	1.4	1.4	−0.1	−5.0	3.6	4.3
1997	1.7	1.5	0.0	6.9	3.6	3.7

Table 7: Interacted Regression Coefficients for Regions (Base Year 1974)

1: Family = 0 Number of Observations:

2: Family = 1 2119188

Years of Schooling	Coef.	Std. Err.	z	P> |z|	[95% Conf.	Interval]
Differential						
Prediction_1	14.0551	0.0049	2890.83	0	14.04553	14.06459
Prediction_2	12.9294	0.0022	5856.39	0	12.92505	12.9337
Difference	1.1257	0.0053	210.81	0	1.115215	1.136146
Decomposition						
Endowments	0.3143	0.0027	117.28	0	0.3090432	0.319548
Coefficients	0.7193	0.0046	155.3	0	0.7102327	0.728389
Interaction	0.0921	0.0016	57.02	0	0.0889092	0.095239

Table 8: Oaxaca Coefficients Overall using U.S. Censuses

1: Family = 0

2: Family = 1

Number of Observations:
2119188

Years of Schooling	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Differential						
Prediction_1	14.0551	0.0049	2890.83	0	14.0455	14.0646
Prediction_2	12.9294	0.0022	5856.39	0	12.9251	12.9337
Difference	1.1257	0.0053	210.81	0	1.1152	1.1361
Endowments						
Europe	0.0534	0.0008	67.08	0	0.0519	0.0550
Asia	0.0696	0.0014	48.31	0	0.0668	0.0724
Africa	0.0233	0.0009	25.89	0	0.0215	0.0250
NorthAmerica	0.0003	0.0003	1.02	0.3	-0.0003	0.0010
SouthAmerica	-0.0145	0.0004	-34.77	0	-0.0153	-0.0136
Mexico	0.1821	0.0018	102.9	0	0.1787	0.1856
Total	0.3143	0.0027	117.28	0	0.3090	0.3195
Coefficients						
Total	.7193109	.0046318	155.30	0	.7102327	.7283891
Interaction						
Total	.0920739	.0016147	57.02	0	.0889092	.0952386

Table 9: Detailed Oaxaca Coefficients Overall using U.S. Censuses

1: Family = 0

2: Family = 1

Number of Observation:

2119188

Years of Schooling	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
Differential						
Prediction_1	11.2232	0.0054	2084.11	0	11.2126	11.2338
Prediction_2	10.1020	0.0026	3857.37	0	10.0969	10.1072
Difference	1.1212	0.0060	187.23	0	1.1094	1.1329
Decomposition						
Endowments	0.1355	0.0018	76.12	0	0.1320	0.1390
Coefficients	0.8962	0.0059	152.51	0	0.8847	0.9078
Interaction	0.0894	0.0019	46.37	0	0.0857	0.0932

Table 10: Oaxaca Coefficients Overall using International Censuses

1: Family = 0 Number of Observation:

2: Family = 1 2119188

Years of Schooling	**Coef.**	**Std. Err.**	**z**	**P¿z**	**[95% Conf.**	**Interval]**
Differential						
Prediction_1	11.2232	0.0054	2084.11	0	11.2126	11.2338
Prediction_2	10.1020	0.0026	3857.37	0	10.0969	10.1072
Difference	1.1212	0.0060	187.23	0	1.1094	1.1329
Endowments						
Europe	0.0743	0.0011	67.11	0	0.0721	0.0765
Asia	0.0304	0.0007	46.15	0	0.0291	0.0317
Africa	-0.0049	0.0002	-22.47	0	-0.0053	-0.0045
NorthAmerica	-0.0770	0.0008	-100.2	0	-0.0785	-0.0755
SouthAmerica	0.0007	0.0002	4.54	0	0.0004	0.0010
Mexico	0.1120	0.0011	99.37	0	0.1098	0.1142
Total	0.135486	0.00178	76.12	0	0.1319976	0.138975
Coefficients						
Total	.896242	.0058765	152.51	0	.8847242	.9077598
Interaction						
Total	.0894481	.0019292	46.37	0	.085667	.0932292

Table 11: Detailed Oaxaca Coefficients Overall using International Censuses

	Difference	Endowments	Coefficients
1974	−0.63	1.22	−1.38
1975	−3.51	−1.13	−2.67
1976	−1.72	0.57	−2.07
1977	2.88	0.28	2.61
1980	3.86	0.43	3.45
1981	3.81	0.50	3.51
1982	3.14	0.85	2.40
1983	−0.43	−0.64	0.17
1984	−0.10	−0.15	−0.17
1985	−0.53	−0.20	−0.32
1986	−1.01	−0.26	−0.80
1987	0.63	0.19	0.43
1988	−1.11	−1.17	−0.03
1989	0.22	0.09	0.18
1990	−0.40	−0.19	−0.11
1991	0.52	0.01	0.67
1992	1.31	0.38	0.97
1993	2.90	0.81	1.81
1994	2.32	1.60	1.12
1995	1.92	0.94	0.95
1996	1.03	0.73	0.41
1997	0.89	0.90	0.00
1998	3.50	0.99	2.52
OVERALL	1.13	0.31	0.72

Table 12: Oaxaca Coefficients using U.S. Censuses

	Difference	Endowments	Coefficients
1974	−2.08	0.84	−1.81
1975	−4.21	−0.71	−4.29
1976	−3.47	0.26	−3.28
1977	2.69	0.09	2.60
1980	3.41	−0.15	3.29
1981	3.28	−0.07	3.61
1982	2.60	0.17	2.53
1983	0.75	−0.47	1.11
1984	−0.50	−0.37	−0.64
1985	0.66	−0.20	0.57
1986	−0.20	−0.02	−0.31
1987	0.16	−0.03	0.19
1988	−0.75	−0.22	0.50
1989	−0.08	0.10	−0.15
1990	−0.79	0.02	−0.67
1991	0.40	0.06	0.50
1992	1.17	−0.06	1.25
1993	2.35	0.11	1.96
1994	1.99	0.86	1.15
1995	1.76	0.57	1.26
1996	1.44	0.60	1.10
1997	0.79	0.43	0.32
1998	2.88	0.55	2.69
OVERALL	1.12	0.14	0.90

Table 13: Oaxaca Coefficients using International Censuses

B Figures

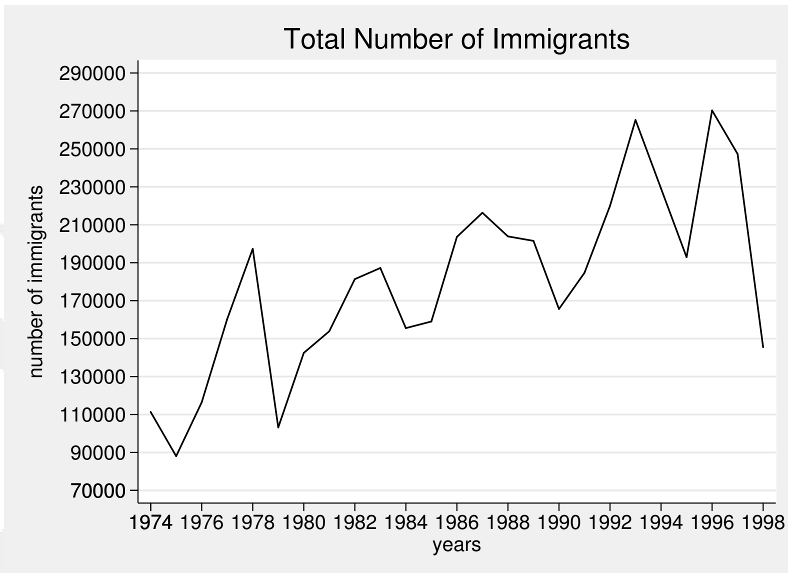

Figure 1: Total Number of Immigrants

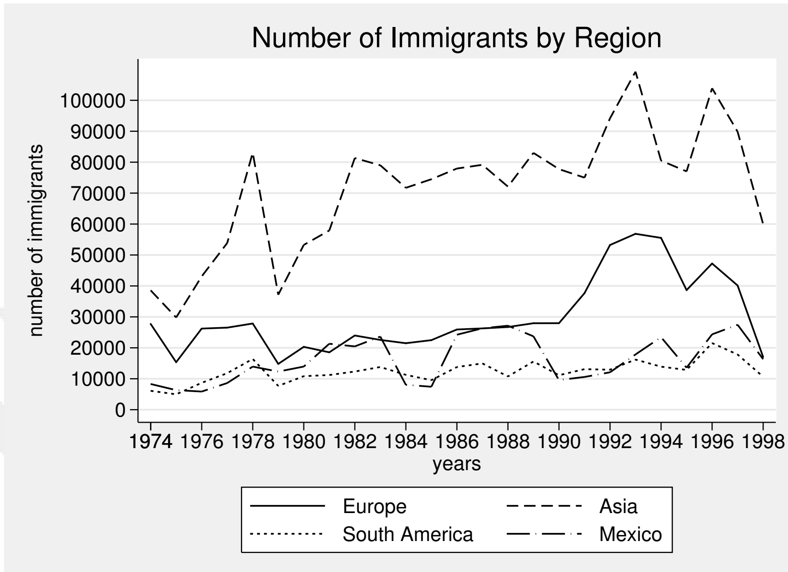

Figure 2: Number of Immigrants by Region

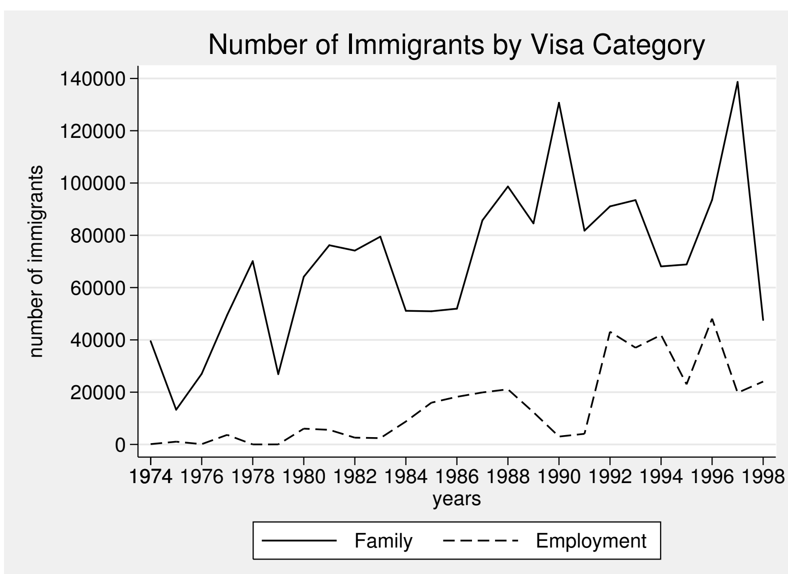

Figure 3: Number of Immigrants by Visa Category

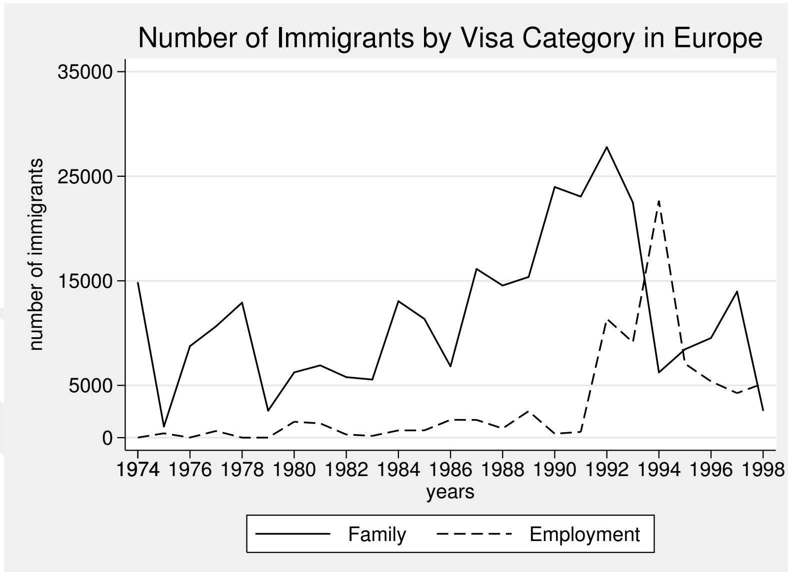

Figure 4: Number of Immigrants by Visa Categories in Europe

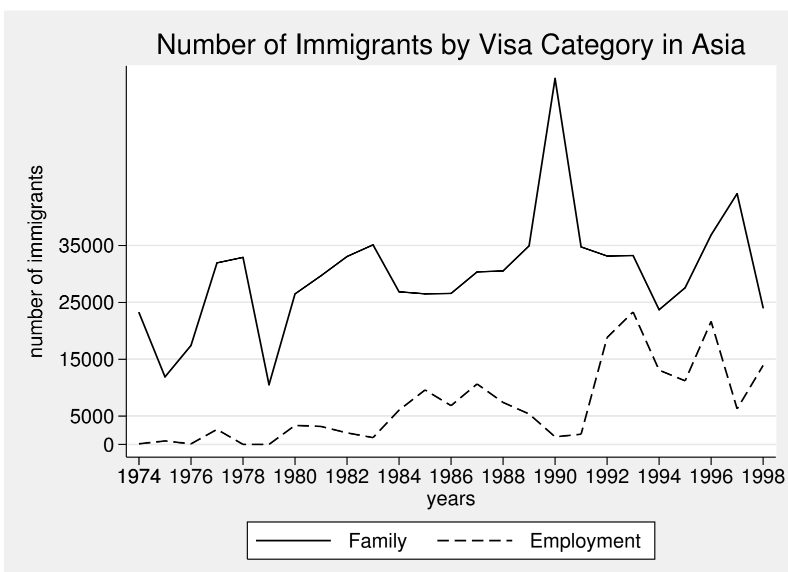

Figure 5: Number of Immigrants by Visa Categories in Asia

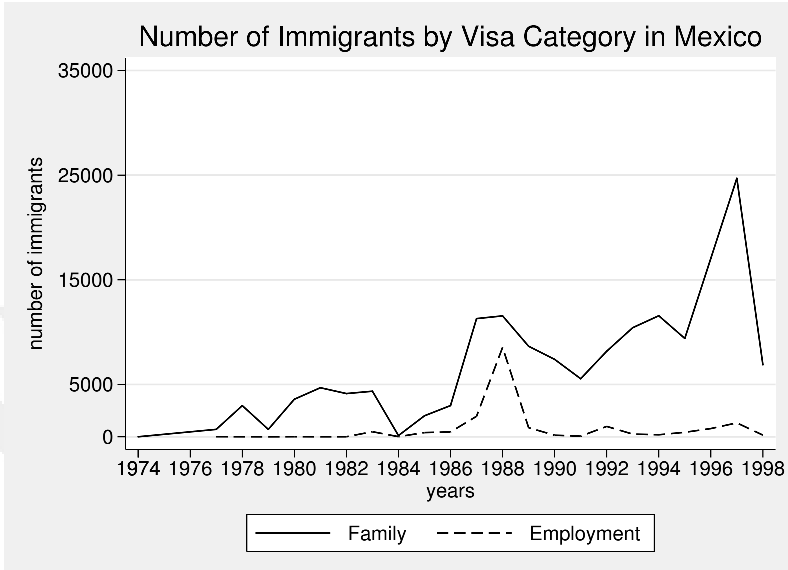

Figure 6: Number of Immigrants by Visa Categories in Mexico

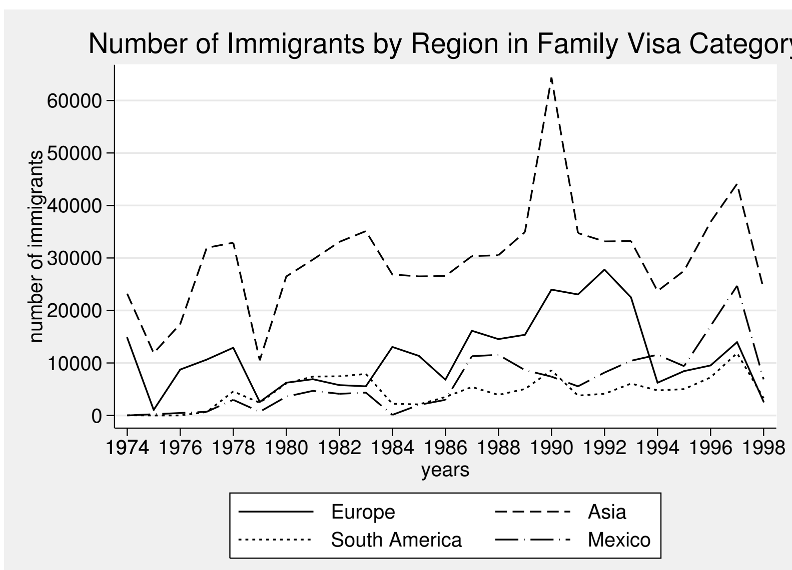

Figure 7: Number of Immigrants by Regions in Family

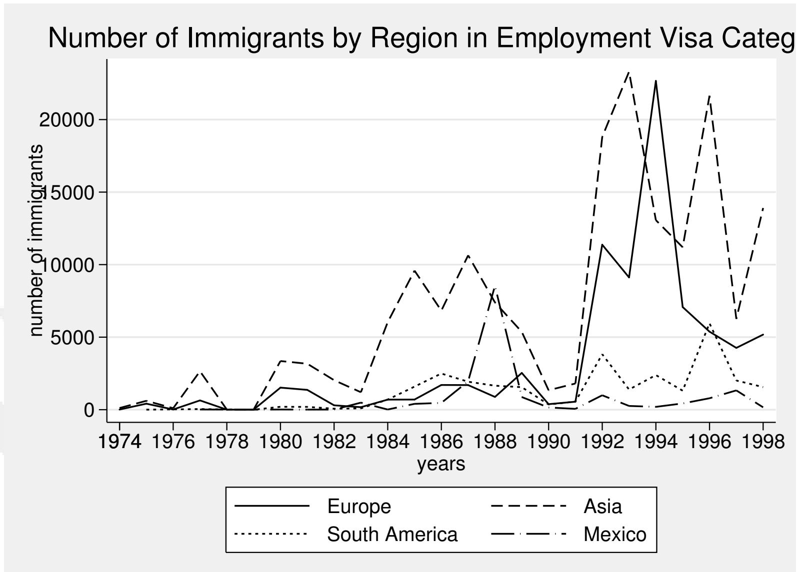

Figure 8: Number of Immigrants by Regions in Employment

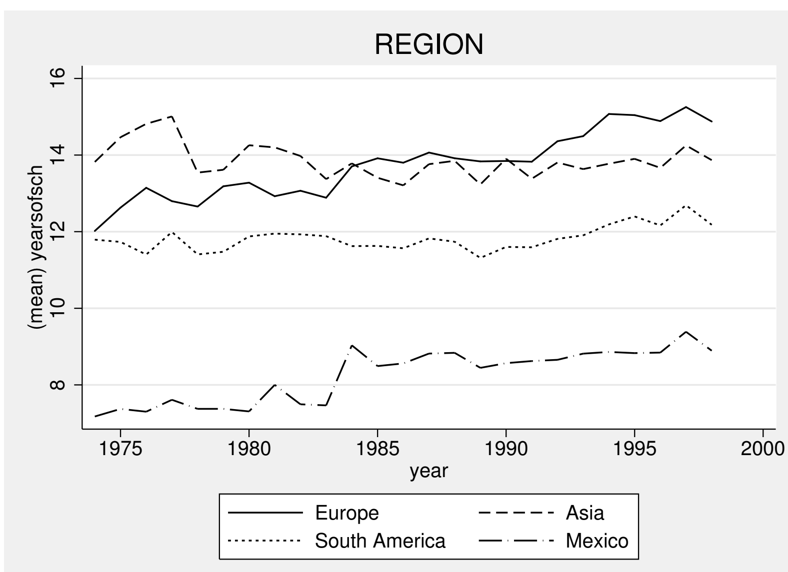

Figure 9: Skill Level by Region using U.S. Censuses

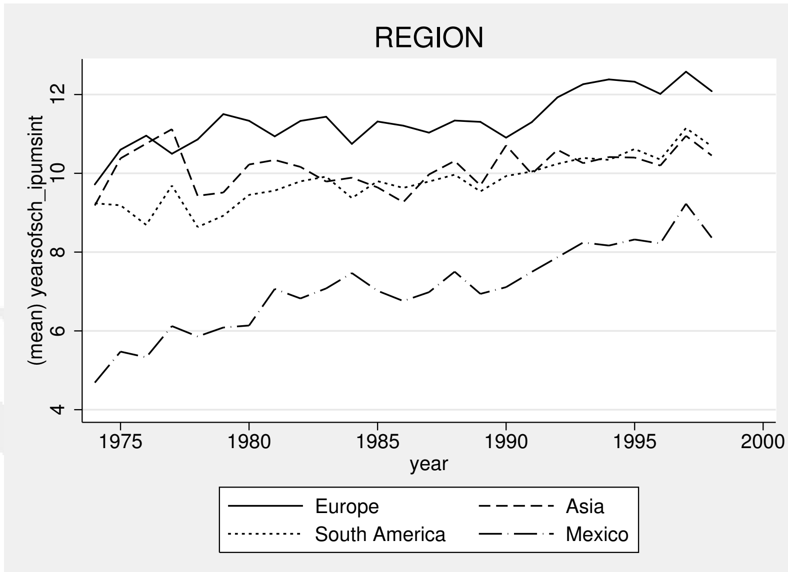

Figure 10: Skill Level by Region using International Censuses

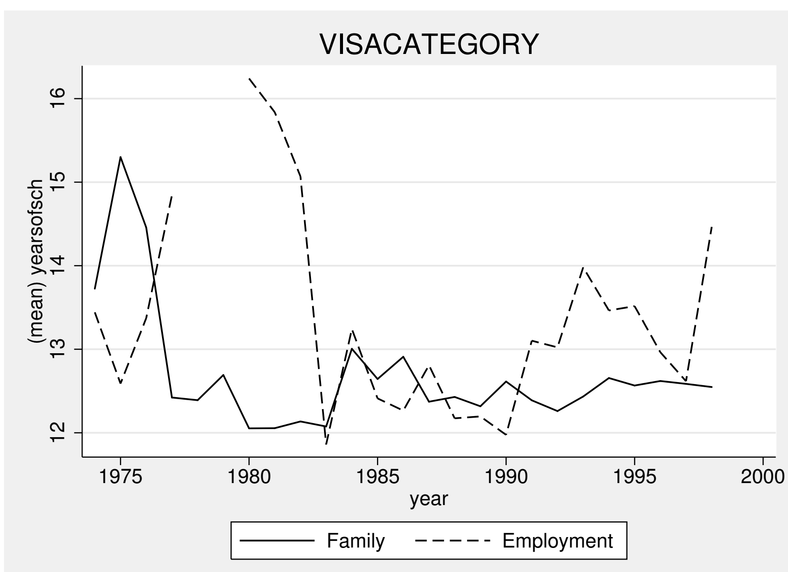

Figure 11: Skill Level by Visa Category using U.S. Censuses

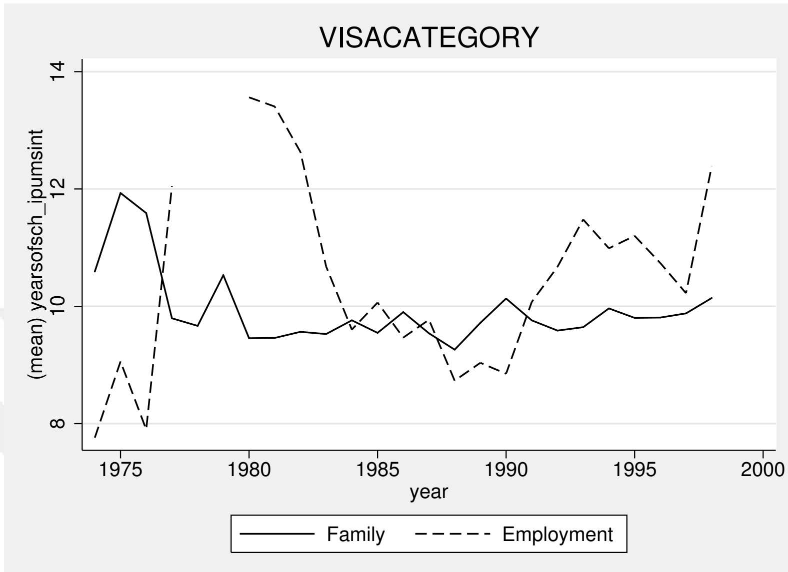

Figure 12: Skill Level by Visa Category using International Censuses

Figure 13: Skill Level in Europe by Visa Category using U.S. Censuses

Figure 14: Skill Level in Europe by Visa Category using International Censuses

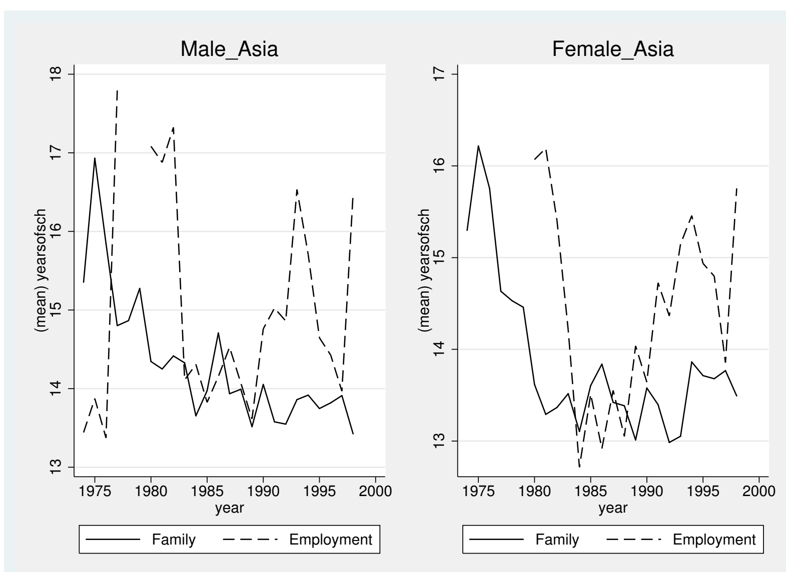

Figure 15: Skill Level in Asia by Visa Category using U.S. Censuses

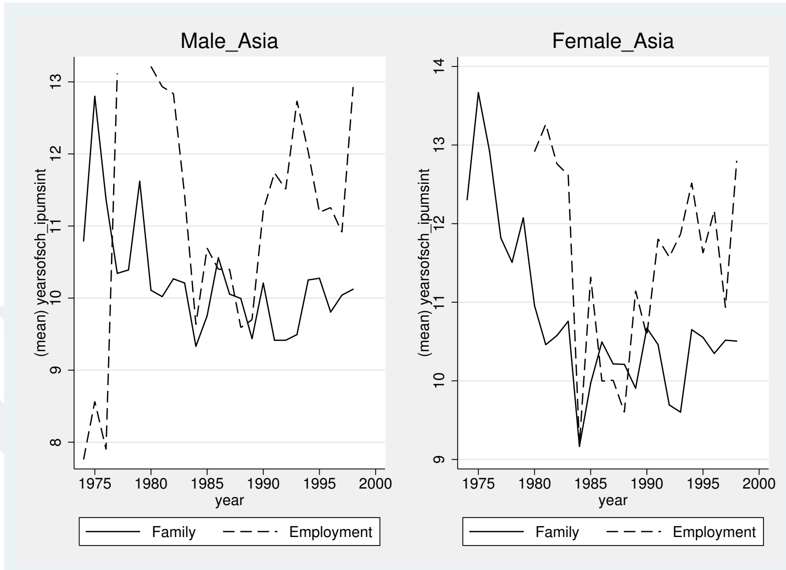

Figure 16: Skill Level in Asia by Visa Category using International Censuses

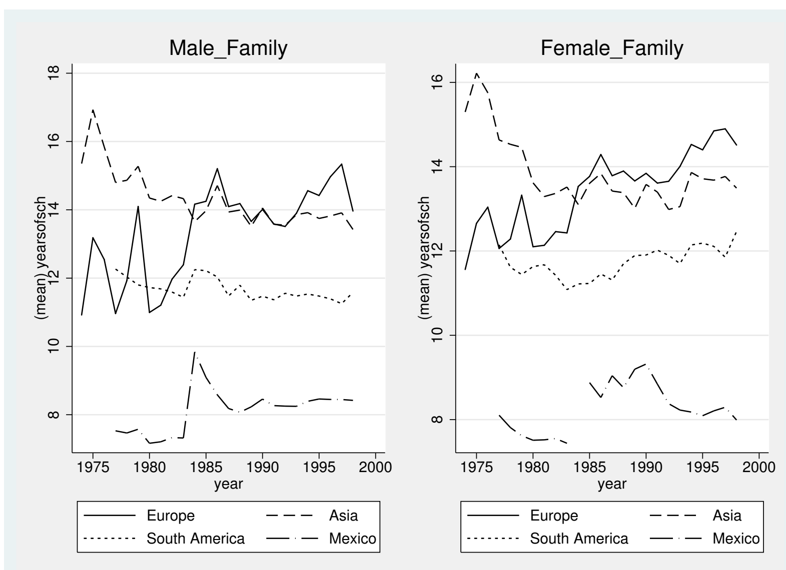

Figure 17: Skill Level of Family Class by Region using U.S. Censuses

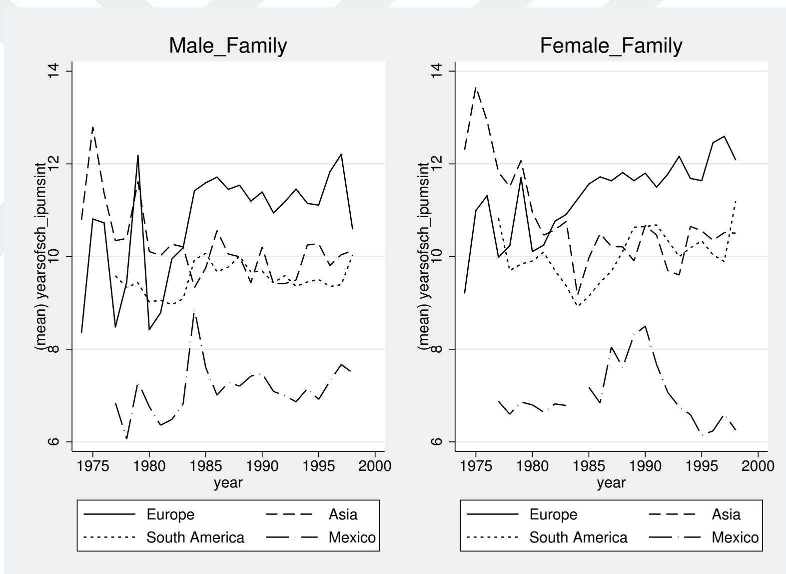

Figure 18: Skill Level of Family Class by Region using International Censuses

Figure 19: Skill Level of Employment Class by Region using U.S. Censuses

Figure 20: Skill Level of Employment Class by Region using International Censuses

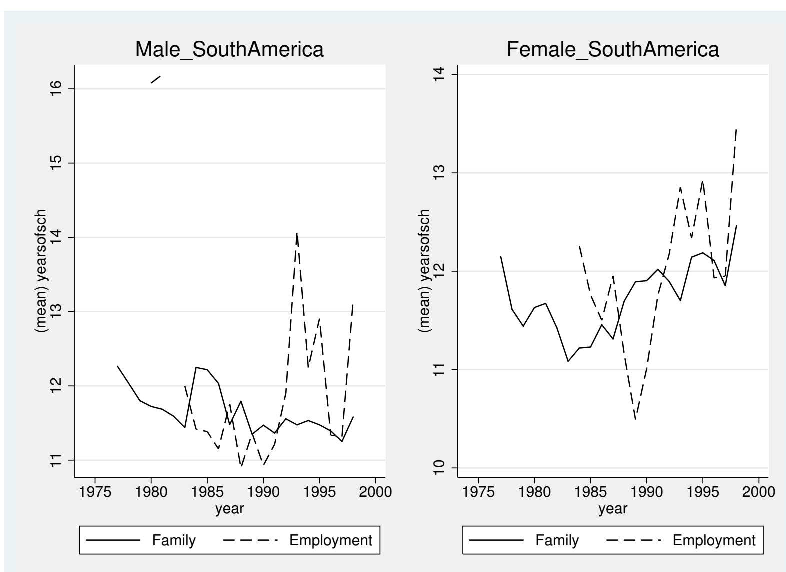

Figure 21: Skill Level in SouthAmerica by Visa Category using U.S. Censuses

Figure 22: Skill Level in SouthAmerica by Visa Category using International Censuses

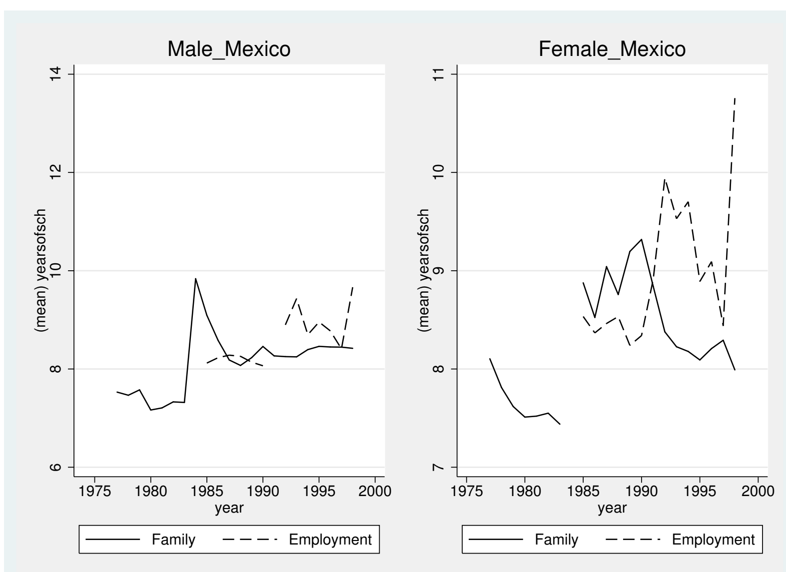

Figure 23: Skill Level in Mexico by Visa Category using U.S. Censuses

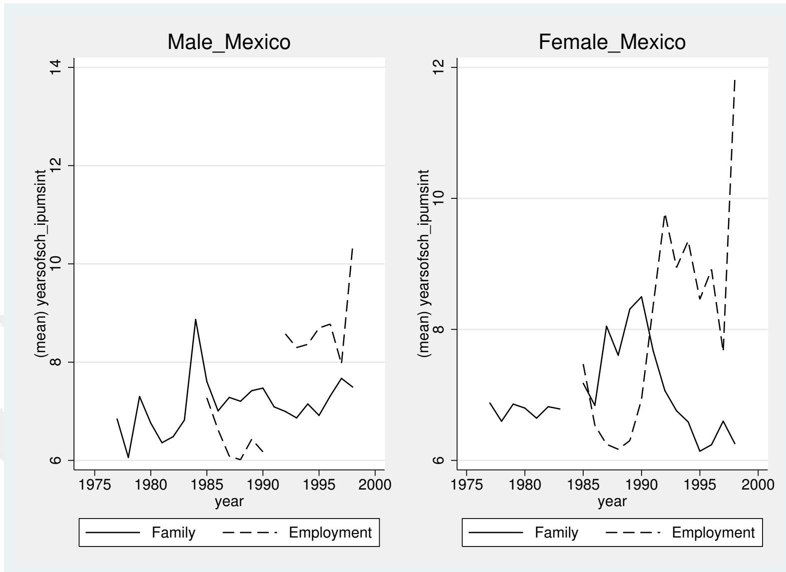

Figure 24: Skill Level in Mexico by Visa Category using International Censuses

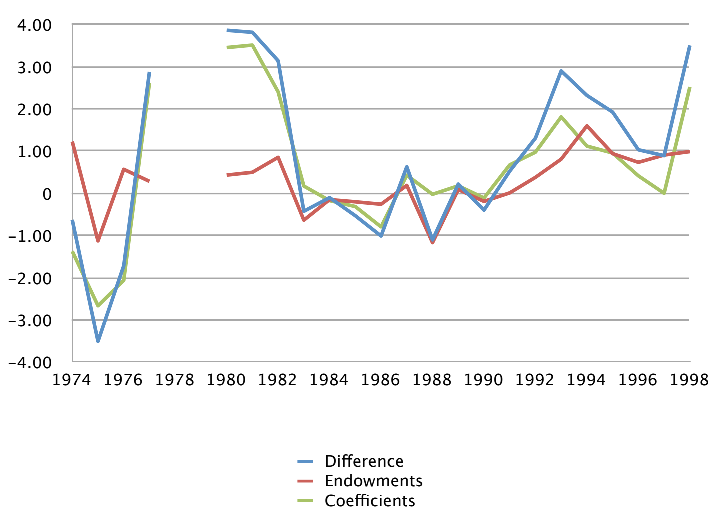

Figure 25: Oaxaca Coefficients using U.S. Censuses

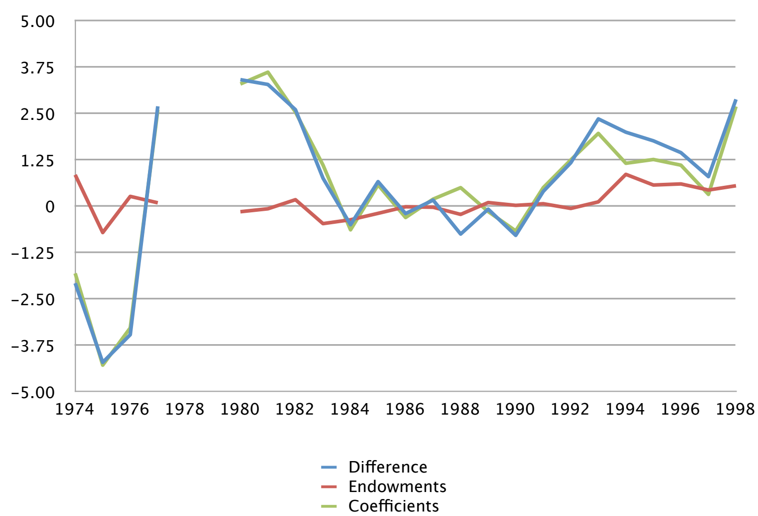

Figure 26: Oaxaca Coefficients using International Censuses