OUTCOMES BY VISA CATEGORY FOR IMMIGRANT WORKERS IN THE UNITED STATES

by

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ABSTRACT

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Keywords: immigration, skilled immigration, visa category, preference system, skill differential

This paper tries to understand the skill differentials of immigrants in the U.S. whose year of immigration is between 1972 and 2000 by using multiple micro level data sets. We mainly focus on multiple effects which determines skill and age levels of immigrants, namely country and visa composition effect. Our results indicate that the skill differentials between employment and visa categories is related to selectivity of employment visa category rather than the differences in regional compositions. After establishing this fact, we examine whether this selection yields beneficial labor market outcomes for immigrants. It is empirically shown that employment visa holders perform much better for all six labor market outcomes which are earned income, wage income, employment status, labor force participation status, poverty status, and English ability.

ÖZET

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EKONOMİ YÜKSEK LİSANS TEZİ, TEMMUZ 2019

Tez Danışmanı: Prof. Dr. Abdurrahman Aydemir

Anahtar Kelimeler: göç, beceriye göre göç, vize kategorisi, göçmen seçim sistemi, beceri farklılıkları

Bu makale ABD'ye 1972 ve 2000 yılları arasında göç etmiş göçmenlerin becerileri arasındaki farkları birden çok data seti kullanarak inceliyor. Çalışmamızın odak noktasında beceri farklılıklarının belirleyicisi olan ülke ve vize kompozisyonlarının etkileri var. Sonuçlarımız farklı vize kategorileriyle gelen göçmenler arasındaki beceri farklılıklarının bölgesel kompozisyonlardaki farklılıkltan ziyade iş vize kategorisinin seçiciliğinden kaynaklandığını gösteriyor. Bu olguyu ileri sürdükten sonra bahsi geçen seçiciliğin göçmenler için faydalı iş gücü piyasası çıktıları sağlayıp sağlamadığını inceledik. Empirik olarak ileri sürüyoruz ki iş vizesine sahip göçmenler kazanılan gelir, ücret geliri, istihdam statüsü, iş gücü katılım statüsü, yoksulluk statüsü ve ingilizce becerisi konularında daha iyi performans gösteriyorlar.

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1. INTRODUCTION

Immigration is one of the most contentious subjects in several traditional host countries. Since most of the immigrants are low skilled immigrants, people blame them for overuse of the social welfare system; in other words, as an additional burden on public resources who create competition for low skilled natives' job opportunities. Especially with the rise of right-wing politics, these arguments are pronounced more often recently. On the other hand, skilled immigration has been rising on the policy agendas of host countries for a variety of reasons. The most striking reason is skilled immigrants are acknowledged as a source of human capital, which has the potential to increase the productive output of a country.

Since the admission of new members into the society plays a crucial role in the efficient use of resources, as well as the future possible productivity of the host country, countries assign great importance to whom they admit. Hence, the labor market outcomes of immigrant workers, the effect of immigrants on the natives' labor market outcomes, and the economic impact of admission policies on the labor market outcomes deserve careful investigation. In this context, host countries' immigration policies provide a fertile ground to shed light on these relationships. Most of the literature on immigration economics is focused on the comparative analysis of labor market outcomes, namely between host countries, between immigrants and natives, and within immigrant groups.

This paper aims diagnosing several important aspects of the immigrant admission process by emphasizing the immigrants' labor market outcomes and skill differentials with respect to the visa categories through which they are admitted. In the first part of the thesis, we study the effect of admission policies on skill selectivity of immigrants in the United States by source region and country, and the resulting skill distribution of immigrant workers. In the second part, we study the extent to which immigration policy shapes the immigrant workers' labor market outcomes through its impact on skill distribution.

In order to identify these effects, we make use of three data sources: Immigration Naturalization Service (INS) data set, Integrated Public Use Micro-data Series (IPUMS) International Census data sets, and the U.S. Censuses, currently known as American Community Survey (ACS), covering approximately a forty five year period starting from 1970. The INS micro level data sets provide a great number of variables in terms of immigrant demographics, and more importantly the visa category by which the immigrant is accepted. The most marked selection criteria for skilled immigrants is their human capital characteristics, which are commonly measured by years of schooling. This data, however, does not contain any information either on years of schooling or other variables related to immigrants' educational achievements.

In order to address this issue, we use the IPUMS International data sets which involve hundreds of countries' census surveys spanning over the last seven decades. They also include a variety of variables that help identify characteristics of individuals. We use this information to form a proxy schooling variable in the INS data. Based on a set of characteristics we compute the mean years of schooling from source country data and match this information to the immigrant sample.

Additionally, using the U.S. Censuses, we again generate years of schooling information and match it with the remaining data sets. This data set provides an alternative measure of immigrants' educational attainments; although it contains fewer source countries in comparison with IPUMS. We use this data set as a robustness check in order to confirm the results.

The remaining parts of the paper are as follows: Chapter 2 reviews the existing literature on skilled immigration focusing on articles in the field related to skill differentials. Chapter 3 discusses data explaining the three different micro-level data sources. In this chapter, we also highlight the way in which we restricted the data as well as the way in which the data restricted our research. The methodology of matching these data sources is another important part of this chapter. Chapter 4 presents descriptive statistics to elicit the current circumstances surrounding differentials in characteristics of immigrant cohorts, immigrants' mean educational attainments, and visa category differentials. Chapter 5 presents the results from the analysis of skill selectivity and skill distribution along with their labor market outcome. The last chapter is devoted to interpretation of the findings.

2. LITERATURE REVIEW

In this chapter, we first aim to highlight papers in the immigration economics literature that discuss the importance of skilled immigration for the host countries and its implications on the source countries, highlighting several comparative studies. We then review papers that conduct a comparison between native and immigrant workers within the host countries. We also discuss the differences between the traditional host countries' immigration policies and compare the outcomes between countries. Finally, we will review the differences in the labor market outcomes across immigrants, therefore evaluating the effectiveness of immigration policies.

2.1. Economic Implications of Immigration

Immigration has a variety of consequences on both sending and receiving countries. Since immigration policies are mostly shaped for the purpose of attracting skilled immigrants, the contribution of these immigrants in economic, social, and political life come into the foreground. Therefore, identifying the consequences of immigration becomes the main aim of researchers for both host and source countries in terms of economic contributions and implications, skill distribution, in other words, human capital characteristics as well as welfare implications. (Bhagwati and Hanson, 2009; Constant and Zimmerman 2013)

A significant outcome of migration is concerning its fiscal implications. It is widely believed that immigrants constitute a burden on the collected taxes of the host country, yet the immigrants' contribution to or exploitation of the fiscal system vary tremendously with respect to their skill levels. Since a large portion of immigrants are of working age, they have the potential to contribute to the fiscal system; however, this hypothetical case does not occur if either immigrants decide not to work or cannot adapt to the labor force due to labor market conditions and benefit from subsidies as a result. The benefit of widening the tax base is decreasing old age dependency ratio which solves a crucial issue in the popular host countries which have aging population. High skilled immigration, therefore, has a positive fiscal contribution since their contribution is larger (Aydemir, 2013). On the other hand, it is claimed that the low skilled immigrants' fiscal implications are the opposite of their skilled counterpart. Not only do they pay less tax, but also benefit more from government services. (Borjas, 1995; Borjas and Hilton 1996; Borjas, 2001; Fix and Passel 2002; Storesletten, 2000). Borjas also alleges that the new immigrant cohorts are exposed to lower entry wages, and therefore, their contribution to the fiscal system is less significant in comparison with previous cohorts.

There are two other repercussions of immigration concerning the source country which are brain drain and remittances. Migration of skilled workers to developed countries has important implications on source countries. The first thing that comes to one's mind is its adverse economic impact on the source country due to the loss of high skilled workers (Commander et al. 2004; Docquier and Rapoport, 2011). Nonetheless, it also has a positive implication which comes from the rising investment in human capital thanks to greater return to educational attainment. (Mountford 1997; Stark and Prskawets, 1997; Beine et al. 2001; Docquier and Rapoport, 2011).

Not only an increase in investments in education is a boon of immigration for the source country, but also remittances constitute an integral part of its positive effects. It is asserted that remittances decrease inequality in developing economies (Adams and Page, 2007). According to the findings of Adams and Page (2007), "remittances reduce the level, depth, and severity of poverty in the developing world," where "a 10% increase in the share of international migrants in a country's population will lead to a 2.1% decline in the share of people living on less than $1.00 per person per day." There is also empirical evidence that the probability of sending remittances rises with respect to human capital level (Stark & Lucas, 1988; Brown & Poirine, 2005). Acosta (2007) claims that remittances decrease labor force participation, but increase entrepreneurial activities among recipients based on evidence from El Salvador.

On a similar issue, Jackline Wahba (2007) suggests in her Egypt-based research that accounting for selectivity biases, evidence indicates that, "temporary migration results in a wage premium on migrants' return. On average, return migrants earn around 38 percent more than nonmigrants."

From Zhao's (2002) standpoint, return migration occupies a great importance in China's economy. One of his main findings is that immigrants invest more in productive farm assets after their return to the home country. Therefore, return migration may play an important role in the modernization process of China.

Consequently, immigration has a diverse set of implications on both source and host countries. Determining the direction of the impact requires empirical investigation and there are controversial empirical evidences as well as consensus about some outcomes. In the next section, we will focus on historical background of debates related to the main findings in immigration literature.

2.2. Developments in Immigration Economics

There has been a tremendous increase in academic interest in issues related to the economic aspects of immigration. The economic impact of immigration policies caught the attention from researchers to point out the causal effect so that it can infer the policy implications.

Barry Chiswick's pioneering paper published in 1978 entitled "The Effect of Americanization on the Earnings of Foreign-born Men" adopted a Mincerian regression model to explore successive immigrant cohorts' labor market outcomes over time with respect to natives. His findings suggested that immigrants earn less than native workers when they initially arrive at the host country but the wage gap decreases over time in favor of immigrant workers. In other words, immigrants' earnings can catch up with natives in a decade after arrival. Initial wage difference, in comparison with the native counterpart, is caused by the immigrants' lack of human capital determined by the new labor market demands. As immigrants invest in themselves in this leads to a rise in wages resulting in immigrant earnings convergence to native-borns.

These results were later challenged in the literature claiming that the convergence in terms of wage between immigrant and native workers is not that significant, so that recent cohorts will probably suffer from a substantial wage disadvantage for much of their working lives (Borjas, 2000). Borjas takes into account the differences in the entry earnings of successive cohorts and finds no evidence that recent cohorts elicit a larger growth in terms of their labor market outcomes.

Borjas accredits a significant interest to decreasing entry wages of immigrant cohorts over time. Based on his findings immigrant workers may not be able to catch up with natives in terms of their wages because much lower entry wages among recent cohorts, despite the immigrants' wages increase within the decade following migration. He also finds that while an average immigrant had 11.1 years of education as opposed to 11.5 for their native counterparts in 1970, this difference has widened recently and has become 11.9 as opposed to 13.2 in 1990. A similar pattern is observed for wages. An average immigrant worker earned 16.6 percent less than his native counterpart in 1970; however, this difference became 31.7 percent in 1990 (Borjas, 1995). The changes in entry wages is also studied in other immigrant receiving countries and yielding similar findings (Borjas and Friedberg, 2009; Baker and Benjamin, 1994; Aydemir, 2003; Aydemir and Skuterud, 2005; Li, 2003). For instance, Aydemir (2003) shows a successive decline in the labor force participation and employment outcomes of immigrants in Canada.

Borjas (1987) also assigns a great importance to the composition of immigrant cohorts' country of origin and claims that conditions in the source country have an integral part in determining immigrants' labor market outcomes. Lalonde and Topel (1992) maintain a similar argument. They argue that the labor market skills of different immigrant cohorts are sahped by the composition of country of origin. Besides, there might be an underestimation problem given that the wages of the natives for low skilled labor who competes with a larger share of immigrant workers, drops significantly while their immigrant counterpart's wage rises (Borjas 1999, LaLonde and Topel 1992). In an examination of within-country and across-country components of skill differentials between immigrant visa classes, Aydemir (2011) finds that over 90 percent of schooling differential between skilled workers and family immigrants, for both males and females, is due to differences within national-origin groups, whereas less than 10 percent is attributed to differences in national and origin composition across the two classes. The findings indicate that the points system does yield higher skill immigration flow through a selection of the more skilled immigrants within the country of origin rather than with changing its composition.

Above studies reveal that immigration policy is influential in shaping immigrant characteristics. In the next section, we aim further focus on recent comparative studies which illuminate the comparison of skill differentials between immigrant and native workers as well as between major host countries.

2.3. Comparative Studies Within and Between Host Countries

The characterization of differences in the skill distribution and labor market outcomes of immigrants in comparison with native-born constitute a fundamental part of a comparative analysis. At the core of migration policies policy makers take into account not only the productivity of immigrants but also the natives' labor market conditions in order to maintain a balanced labor market since the immigrants' main implication is to change the proportion as well as the characteristics of the factors of production in the receiving country by their labor supply.

Consider the following case as an example of the extent to which immigration flows may alter the intrinsic features of a labor market, thereby the economic opportunities for natives. The civil war in Syria has culminated into a major refugee crisis in its neighboring countries, and Turkey has been receiving the greatest number of refugees and asylum seekers since the civil war started. There are a few outcomes of this exogenous labor supply shock on the labor market outcomes of natives on which the whole literature compromises. These include adverse effects on the labor market outcomes of unskilled natives who have to compete with Syrian refugees, net displacement from the labor market and declining earning opportunities for the low skill natives, mobility from informal to formal, as well as, from treatment regions to comparison regions. (Balkan and Tumen, 2016; Ceritoglu et all. 2017; Del Caprio and Wagner, 2015; Tumen 2016) Such negative effects would not be desirable for policy makers. Of course, this example constitutes an extreme in terms of the extent of labor supply shock. Such labor market consequences, however, characterize an integral part of policy making when it comes to immigration. The admission policy that host countries should pursue, therefore, deserves special attention to labor market compatibility of immigrants.

There is a large number of theoretical models justifying this issue (Chiswick, 1982; Borjas, 1987), but empirical evidence varies significantly. Borjas claims that change in characteristics of immigrant cohorts may explain the decline in wages of less skilled natives. Jaeger (1996) agrees with Borjas, whereas Altonji and Card (1991) find no relevance between these two events. Nonetheless, Borjas et al. (1997) and Batalova (2006) also recognize that high skilled immigrants have a small effect on native workers' wages.

The large size of immigrant stocks across countries contributes to the significance of this issue. According to the International Migration report published by United Nations in 2017, the share of foreign-borns represents approximately 15 percent of the population in the United States, 22 percent in Canada, and 28 percent in Australia. These proportions increase tremendously when the second generation of immigrants is included. Given these large shares of foreign-born people, the examination of labor market outcomes draw attention in the structuring of admission policies.

Family reunification purposes, skill based as well as humanitarian concerns, are key factors in immigration policies. The relative weight of these visa classes reflects host countries' preferences and empirical analysis of this issue attracts a lot attention in the literature. When viewed from this aspect, comparative studies shed light on the outcomes of different policies. These studies compare immigrant and native workers or different immigrant groups either within a host country and across host countries.

US immigration policy has traditionally given more weight to family related preference. On the other hand, the remaining major immigrant receiving countries, such as Canada and Australia, which are considered the counterparts of the US in comparative studies, emphasize skill-based admissions and rely on a points-based system for selecting high skilled migrants. This system provides a well-defined identification for the immigrant selection process in order to maximize the benefits of host countries as well as a rapid adjustment of human capital of immigrants. Immigrant selection is based on immigrants' observable characteristics such as age, experience, credentials, and English proficiency in Australia (Boucher 2013, Miller 1999). Similarly, in Canada, the points system is based on age, education level, occupation and experience level of immigrants (Constant and Zimmermann, 2013), which determine whether the immigrant is admitted or not.

Aydemir (2012) indicates that 65% of the visas are allocated for skilled workers as opposed to 27% for family ties in Canada. The rest is dedicated to refugees and asylum seekers. Although the point system provides a selection criteria based on the objectives set by the country of destination, it does not take into account unobservable characteristics which might significantly affect the labor market outcomes of immigrant workers.

Since all of the host countries have been seeking to improve their immigration policies, studying the differences between the outcomes of alternative policies poses an integral implication on policy configuration. In order to turn these immigrant flows into an opportunity, all traditional immigrant host countries are contemplating expanding the policies which have favorable outcomes for attracting skilled immigrants. Even though economies of these three counties are very similar in many aspects, labor market and immigration policies differ remarkably. These differences provide fertile ground for identifying the labor market effects of various policies through cross country comparisons. These comparative analyses may also shed light on how ongoing changes in policies perform in traditional host countries.

In the United States, concerns have arisen over the declining education and skill levels of successive waves of immigrants. Such concerns have also prompted proposals to introduce more explicitly skill-based admissions criteria like those used in Australia and Canada. In order to address anxieties over the declining education and skill levels of immigrant waves in the US, researchers and policymakers have begun to propose the introduction of skill-based immigration selection in the US, as is the case in Canada and Australia. Although this approach contrasts the current family reunification emphasis in the US immigration policy, there is empirical evidence that implies that such selection criteria would be economically, politically, and socially beneficial.

In an earlier attempt to understand the effects of alternative immigration policies on immigrant outcomes, Duleep and Regets (1992) analyze cross-country differences in language fluency, education, and labor market outcomes of immigrants in light of differences in immigration systems. They find that the Canadian immigrants language proficiency does not turn into either an education or an earnings advantage relative to their US counterparts. Besides, the percentage of family-based immigrants and the initial earnings of immigrants have an inverse relation. This result highlights the fact that employment-based immigrants have the advantage of receiving higher wages at the beginning of their migration process. This difference tends to diminish in time due to the higher earnings growth of family related immigrants. They concluded that the Canadian points-based system has no effect on immigrant education and earnings.

In contrast to above findings, by pooling immigrants across all source countries, Borjas (1993) finds that immigrants in Canada are, on average, more skilled than immigrants in the U.S. Although this results in an earnings advantage for Canadian immigrants, the difference disappears once immigrants from the same source country are compared. Canadian immigration policy differs in the mix of source countries rather than increasing skill level from a particular source country. Borjas concludes that this compositional effect explains most of the observed differences in the educational attainment and wages of immigrants in Canada and the United States.

Similarly, Antecol et al (2003) compare Canada, Australia and the U.S. in an attempt to explain whether an immigration system based on skills alters the skill composition of immigrants from a particular source country. They find that relative to natives Australian and Canadian immigrants have higher levels of English fluency, education, and income, than US immigrants. However, after excluding Latin American immigrants, the observable skills of immigrants are similar in the three countries. Hence, this result yields a very similar conclusion that the differences in skill levels are a result of the different national origin compositions of immigrants.

Hence, these studies refer to the point system as a potential source of differences in immigrant characteristics between these countries, and the above results show that screening immigrants generates more educated and language proficient immigrants. The most important contribution of these studies to the literature is the finding that the educational attainment of immigrants in these host countries from the same source countries are indeed very similar.

In addition, while questioning these differences in outcomes, it is crucial to remember that there are significant differences in the selection criteria of Australia and Canada. The Australian point test requires certain factors which are mandatory such as a mandatory pre-migration English-language test. Clarke and Skuterud (2013) correlate the success of the labor market performance of recent cohorts of immigrants to Australia in comparison with their Canadian counterparts. After taking into account these broader entry conditions, they compare immigrants from a common source country and find no remaining evidence of superior employment or earnings outcomes for Australian immigrants. They also find that Australia's selection criteria shift the source country’s distribution of recent arrival cohorts, rather than containing higher quality migrants from within source countries.

Antecol et al. (2006) consider the same subject from another perspective and estimate the effects of time in the destination on male immigrants' wages, employment, and earnings. They compare the change over time in the gap between the native and immigrant populations with respect to employment and wages in Canada, Australia, and the U.S., and find that the total earnings' assimilation is greatest in the United States and the smallest in Australia. Authors emphasize that the new immigrants' wages recover faster over time in the US than in Australia and Canada, and the improvement in employment status is larger in Australia than it is in the other two countries, with Canada falling in the middle in both cases.

In the same context, Jasso and Rosenzweig (2005) investigate employment-based immigrants in Australia and the United States to investigate the main determinants of the size and skill composition of employment-based immigrants and identify the key roles of skill prices and proximity. The hypothesis they test is whether the sending-country conditions and thus immigrant self-selection on the basis of economic gain dominate in determining the skill composition of employment immigrants. They find that key determinants of the size and skill composition of immigrant flows are how skills are priced in different countries and their proximity. According to them, there is no evidence that the differences in the selection mechanism used to screen employment migrants in the two countries play a significant role in affecting the characteristics of skill migration.

Zimmerman et al. (2000) draw attention to another point about migration policies' outcomes. In terms of the reception and attitude towards immigrants by natives, data analyzed from 12 OECD countries shows that the natives in countries which employ skill-based immigrant selection are more prone to believing that immigrants are good for the economy in comparison to the natives of countries that mainly receive asylum seekers and refugees. Still, both cases produce different anxieties in the native population: while natives in Canada and New Zealand show concern over their place in the labor market being negatively affected by immigrants, natives of countries that receive more non-economic migrants show concern over increasing crime rates. In order to manage the sociopolitical and the economic aspects of migration, in terms of moderating social tensions and improving the country's economic performance, the paper concludes that governments in Europe ought to select migrants based on the needs of the labor market. Finally, the research has shown that due to their rapid adaptation and the transferability of human capital, immigrants from countries which share similar attributes with the host country (including language, economic status, and educational outcomes) tend to perform better in the labor market.

The available evidence on relative labor market success of immigrants shows that there are controversial circumstances concerning the outcomes of distinct policies. This growing literature obviously deserves more research in order to identify the effects of various alternative policy implications.

2.4. Comparative Studies across Immigrant Groups

More importantly, another growing literature emphasizes identifying the differences among immigrants in terms of labor market outcomes and skill distribution. This line of research not only allows researchers to elucidate the differences of immigrants' outcomes, skill selectivity, and skill distribution trends across a variety of groups, but also it gives insights to policy makers in order to promote the host countries admission policies based on empirical evidence. One of the ways to divide immigrants into subcategories is using their admission categories, or in other words, their visa categories.

Admission policies were restricted by national quota system before the 1960s in both the US and Canada (Borjas, 1990; Borjas, 1993; Boyd, 1976; Keely and Elwell, 1981). Yet, these policies changed remarkably during 60s. The U.S. replaced the quota model with the preference system via the Immigration and Nationality Act of 1965. Therefore, US immigrant cohorts which arrived before and after 1965 are exposed to a different admission law due to the major change in the immigration policy which may potentially have affected the criteria by which they were admitted. A large immigrant flow has been observed after the change in the immigration law since the new law placed an emphasis on family reunification purposes and on attracting skilled labor rather than a geographic quota model. The 1990 Immigration Act in the US caused immigrants to gain more importance (Batalova, 2006), wherein the new regulations allowed for an increased number of legal immigrants and immigrants admitted under the employment visa category (Martin, Chen, & Madamba, 2000; Beach et al 2000).

Consequently, US immigration policy is mainly divided into two categories: family based, and employment based. Although one of the main aims of changes in immigration policies is to attract more skilled immigrants, therefore to increase the level of skills among immigrants, no official selectivity in terms of observable variables of immigrants is implemented by the new law. At this point, it is worth addressing the labor market outcomes of immigration policy in terms of skill distribution of immigrant cohorts and their labor market outcomes given that immigrants constitute a significant share of the population.

Canada also came up with a similar immigration policy change and abolished the previous quota model of the 1960s. The famous point system was established in 1967 (Green and Green, 1995). Aydemir (2011) investigates immigrants' visa category, education level, and language proficiency at their arrival in Canada in 2000, and concludes that immigrants who are admitted under the skill worker class have higher educational attainment than those admitted under family ties, for both genders. A similar pattern occurs for linguistic abilities. These results highlight that the points system has improved qualifications of Canada's immigrant pool. Although both Canada and the US focused on the manpower potential of immigration in the late 1960's, Canada's emphasis on skills was more observable, whereas for the US it was rather used as a gate-keeping tool, than for skill screening. (Borjas, 1993; Boyd, 1976; Beach et al., 2007).

In the US, despite the fact that aliens with extraordinary skill categories implicitly require skill qualifications, the portion of this category is negligible in light of the overall admission categories. Similarly, even though employment-based visa categories, which are designed to admit immigrant workers with the help of a US employer sponsorship, occupy a larger scale than immigrants with extraordinary abilities, its overall fraction becomes less significant when it is compared with family related visa categories. Borjas (1993) maintains that only 20% of visa categories is put at the disposal of skill-based immigrants, and as one might guess, most of the remaining categories are allocated to family based visa categories, given that visa categories which are accredited to humanitarian purposes span an inconsequential share with respect to the entire immigrant pool.

Additionally, if the employment-based selection leads to higher skills, the channels through which this result emerges in interesting. Since the main choice in terms of policy is between employment and family-based immigration, a comparison of outcomes across the main visa categories can elucidate the main determinants of ongoing debate on the skill selectivity. This helps us understand the potential opportunity cost of both visa categories. This is the reason why this study focuses on the aforementioned outcomes.

3. DATA

In this chapter, we describe the data sets that we use in this study. We will first explain in detail which data set contains what kind of variables, and which one is used for what reason. We will also discuss the restrictions of data sets, as well as the constraints that we impose.

3.1. INS, IPUMS, US Census, and ACS

In this paper, we use a variety of data sets for our analysis. Data from INS (currently known as the United States Citizenship and Immigration Services (USCIS)) is provided by the United States Department of Justice and includes a large number of variables on characteristics and demographics of immigrant workers who become permanent residents of the United States. We use US Censuses (later followed by ACS data) published by the Census Bureau, as well as, the Ipums International Censuses to extract educational information for immigrant workers. These data include characteristics of immigrants that reside in the U.S. and characteristics of source country populations, respectively. As Borjas (2000) indicates, these data sets, especially the U.S. Censuses and INS data, have been the *"work horses"* of the immigration economics literature in the U.S. The combination of the three data sets provides a fruitful source to investigate skill differentials and labor market outcomes of immigrant workers in the U.S.

The INS data is collected by the U.S. officials when either the immigrant workers enter the U.S. as new arrivals or when they adjust their immigrant status within the U.S. This data set provides a number of advantages that facilitate the analysis of immigrant outcomes. The data set includes all legal immigration admissions rather than a subsample. In addition, it supplies rich information on admission category of the admitted immigrant workers for each year from 1972 to 2000. Since this information is recorded every single year, there is no need to divide the data set into time intervals, which helps us to generate more reliable results. Even though the way that admission categories are registered have evolved considerably over years, it is possible to restructure this information to obtain a consistent variable over years without imposing many restrictions. Given that our main concerns are to investigate the impact of admission categories on the labor market outcomes and the skill distribution of immigrant workers, the visa category information is a key variable. The data also includes information on occupation and country of birth of immigrants. Although rich in these aspects, INS data lacks information on immigrant skills. Unfortunately, unlike census data, the information about immigrants' educational attainments and retrospective income is missing in this data set which forces us to combine multiple data sets in order to extract the average of years of schooling variable and process a matching procedure to be able to construct a proxy variable in the INS data set. Also, the occupation variable is considerably aggregated in the INS data starting from 1983, yet a larger restriction is imposed by one of the remaining data sets namely IPUMS International Dataset that we use which makes the INS occupation aggregation less of a concern.

The Integrated Public Use Micro-data Series, referred as IPUMS, provide a detailed number of variables from demographic to educational, occupational characteristics in both personal and household levels, and allow researchers to combine an abundant number of samples into one data set. This data makes use of countries' census surveys all over the world which is highly beneficial for research purposes for a variety of reasons. Although most variables, if not all, are recorded with respect to the states' preferences, which makes them inconsistent with each other and over time, IPUMS International data base convert some of these variables into internationally consistent variables, both across countries and over time periods.

Occisco (Internationally standardized occupation variable) is one of these variables that is consistently coded. However, the standardization process is costly. It imposes many restrictions upon relatively rich data sets. Consider a case in which there exist only two countries, namely A and B. Country A classifies its citizens' occupational information under 800 categories; this classification consists, however, of 10 categories for country B. Thus, country B implicitly imposes a restriction in order to obtain an internationally consistent occupation variable. This is one of the main limitations that we needed to deal with. To incorporate multiple data sets into one in order to extract the lacking information for a variety of data sets, in other words, to conceive an index for occupations of immigrant workers, we needed to use the most restricted variable as the base, such as occisco which only contains 11 groups of occupational information 2 of which, namely armed forces and other occupations, are irrelevant for our analysis. We therefore map all of the occupational codes under these 9 groups. All the remaining data sets are rearranged with respect to those 9 groups.

The standardized variables, on the other hand, facilitates identification of educational attainment information of immigrant workers with a convincingly large data set which originally involved 181 countries before any restrictions were imposed. The data set comprises every possible census data from 1960 to 2010 for these 181 countries. We make use of this massive data set based on specified characteristics and restrictions to obtain the mean years of schooling for as many countries as possible.

Lastly the U.S. Census data contains variables on immigrant characteristics as well as a detailed occupation variable. Since Census data includes the whole U.S. population, we restricted the sample to only foreign-born who are our main interest in this analysis. Occupation variable is rearranged to obtain a consistent variable with respect to IPUMS International which is the base data set in terms of occupation. Years of schooling variable is generated from detailed educational attainment variable by assigning the number of completed years with respect to obtained credentials. Thus, this data set serves a robustness check in order to confirm the results found via IPUMS international. We impose the same restrictions to US Census data as IPUMS data on occupation and years of schooling variables which are explained in the following section.

3.2. Restrictions on Data Sets

In the INS data set, there are three alternative origin country related variables representing similar sets of information which are: country of chargeability, country of birth, and country of last permanent residence. As one might infer from their names, the correlation is very high between these variables. Therefore, we only take into consideration the country of birth variable.

There is also a challenge in the way the variable is recorded, which is caused by the changes in borders of some countries as a result of the Cold War. The countries that emerged as a result of changing borders are coded under the countries that existed prior to their dissolution, namely, Czechoslovakia, Soviet Union, Yugoslavia. Also East and West Germany is code as Germany, and similarly countries/regions under United Kingdom are classified together.

Although for a long period the class of admission variable is recorded in detail, the number of categories is more aggregated for more recent years. Thus, we grouped this variable into four categories: Family Related Preferences, Employment Based Preferences (Major), Employment-Based Preferences (Families) and Refugees. Regrettably, the distinction between major applicants and their families in the employment-based category disappears for 1999 and 2000, and therefore we generated another variable without making the distinction between major applicant and their families to obtain a consistent variable for the entire period, but kept the variable with distinction for a detailed investigation for the years it is available. So, the aggregated visa category variable consists of three categories which are Family Related Preferences, Employment Related Preferences and Refugees.

Regarding the IPUMS International Data Set, there are a number of constraints. Given that the occupation variable it contains is the base variable for the remaining data sets and other relevant variables are defined very similarly, if not perfectly, the only variable to deal with is country of birth. The INS data's country of birth variable is used as a base which required a few minor arrangements. South Sudan and Sudan; Ethiopia and Eritrea; Eastern Samoa and Samoa; Israel and Palestine are unified to provide a consistent variable across data sets.

We rearranged educational attainment information to make it more suitable for my analysis which requires consistent educational attainment variable both across data sets and over time. We thereby generated a years of schooling variable for all the data sets which consist of educational information. This years of schooling variable is the main variable which qualifies immigrants skill level in this research.

Most importantly, we dropped from the analysis the countries for which the years of schooling variable was either missing or its number of observations were too few. We then proceed with a similar process for the occupation variable and drop countries from the data set which have insignificant number of observations. Given that IPUMS data includes only census data, these restrictions make sense. Consider a country which offers a census data set, but there are either less than a thousand years of schooling observation or less than a few thousand occupation observations, or both. Generating the mean year of schooling by disaggregated demographic characteristics from a small sample may lead us unreliable estimates. To avoid this issue, these countries are dropped from data sets although it costed us a considerable number of countries, mostly either island countries or countries in Africa. Even though this restriction deteriorates the comprehensiveness of the paper, we opted for a restricted sample with reliable information, than a less convincing outcome with a larger sample. These restrictions are also applied to the U.S. Censuses in order to possess consistent variables in each data set.

Another limitation is introduced to the age variable. We restricted this variable to working age, which is usually considered ages 25-65. Thus, we imposed the aforementioned constraint with respect to the generated variable. Since the main aim of this study is to analyze the impact of visa category composition on immigrants' characteristics and its resulting labor market outcomes, this restriction makes sense and highly consistent with the existing literature. Hence, we will impose age restriction to every single data set that we intend to use throughout this study for avoiding any potential discrepancy.

We have tried to impose the same restrictions to all of data sets that we use throughout this research, yet this intention has failed when arranging the country of birth variable because the countries that each data set contains differs significantly with each other. Since we will be using multiple combinations of these data sets such as INS-IPUMS and INS-US Censuses throughout the analysis, having the same sample in terms of country of birth of immigrant workers would provide results which are not due to the differences in the sample.

One way to deal with this problem was to impose a country of birth sample which is obtained by the intersection of three data sets in terms of country of birth variable. In other words, we could have used countries which exist in three data sets and drop the remaining countries even if two pairwise data sets both include this country. We first tried to impose this restriction because we did not want any potential misleading biases caused by the differences in comparative samples, yet this restriction was very costly. Since we did not want to lose those countries which exist in two different data sets, but lacks in the third one, we allowed the country of birth variable sample to differ across data sets. Relaxing this restriction increased the number of countries considerably. Our descriptive statistics using information from each pair wise data shows that this difference does not yield to any appreciable differences. We will discuss this issue in more detail in the following chapter.

Until now, we explained the arrangements in data sets for the first part of the analysis in which we demonstrate the differences in the skill and age levels of immigrants with respect to their visa classes. In the second part of the study, we will make use of American Community Survey (ACS) data to discern whether these differences have any meaningful implications in the labor market. In this part of the study, we will generate a visa category fraction from INS data set and implement this variable to ACS data set. The matching process will be discussed in the following subsection.

For this second part of the analysis, we will only make use of ACS data which starts in 2000 and is recorded every year until 2017. US Censuses provides a similar set of variables, however, the way year of immigration is recorded alternates with respect to different Censuses. The intervals take place before ACS and these intervals changes from 2 to 6 years which makes it impossible to decompose them due to a lack of detailed variable. Since we did not want to lose detailed analysis in terms of year of immigration we decided to use only ACS data which provides exact year of immigration information. Since the sample starts in 2000 because of the lack of exact year of immigration information, the first time that we observe the labor market outcomes of the immigrant who arrived in 1972, is in their 28th years in the U.S. Given that we combine all the ACS data set and obtain an average value for each outcome including wage related outcomes, employment status, labor force participation rate, English ability, and poverty, immigrants who arrived more recently may seem relatively disadvantageous because of their year of arrival. To avoid this issue, for descriptive graphs regarding labor market outcomes we drop the labor market outcomes of the first five years after arrival. Thereby, for example, the range of observed outcomes lies between 5 to 17 years for the immigrant who arrived in 2000 in our sample. The interpretation of this restriction will be discussed in the following sections.

3.3. Matching Process

Since there is no variable indicating the skill levels of immigrants in the INS data set, we generate a proxy for the educational level of immigrants based on birth year, gender, country of birth, and occupation. This proxy is created using two alternative data sets - the IPUMS and the U.S. Census data sets-by estimating mean years of schooling based on above characteristics. We then merge this information to the INS data.

The IPUMS data contains relatively similar set of variables for each year from 1960 to 2010. We first restrict the data set's range with respect to INS data, then impose restrictions that we specified for the INS data. Then, we estimate the mean years of schooling variable by birth cohorts (5 years intervals), sex, country of census, and occupation to obtain the mean value of years of schooling for each cell determined by these characteristics. The mean values matched to the INS data forms what we call as "main data set" throughout this paper.

We call a second matched data set that we call as the "supplement data set". This supplement data set is generated analogously to the main data set. Using the US Census and ACS files starting from 1980 to 2017, we estimate the mean years of schooling by occupation, sex, and country of birth among immigrants. We then match this information with the INS data set.

In the second part of the analysis, we study the extent to which labor market outcomes of immigrants differ with respect to immigrants' visa categories. Since immigrants' labor market outcomes can only be observed after their arrival, we use ACS data set which provides a considerable number of variables regarding labor market outcomes. Yet, this data set is missing visa category information which is crucial to our analysis. Thus, for groups of immigrants in ACS data identified by year of immigration, sex, and country of birth, we generate visa category fraction (i.e. family related visa categories, employment-based visa categories and refugees) using the INS data set. Therefore, ACS data set is appended with information on visa category fraction which adds up to 1 for each year of immigration, sex, and country of birth combination along with the variables regarding labor market outcomes. We will call this data set the final data set through this paper.

In the final data set, we generated hourly earnings for both earned income, which includes wage income and self-employment income, and wage incomes. These variables were registered on an annual basis. To compute hourly values, we made use of usual hours of work per week and the number of weeks that the immigrant worked last year. We divided the annual income r by the multiplication of usual hours and the number of hours worked last week.

Since our analysis includes multiple cross-sectional data sets distributed over many years, it was necessary to adjust earnings for each cross section. We used Consumer Price Index of 2000 to turn nominal earnings into real earnings. Besides, the way ACS data registered was based on fiscal year, and it was also necessary to adjust time intervals to annual years.

Labor force participation and employment status are both categorical variables which take value 0 if the immigrant is not in labor force and not employed, respectively.

Poverty variable can be considered as a continuous variable as it takes values from 1 to 501. Poverty was created using detailed income and family structure information about each individual and calculating the family income as a percentage of the appropriate official poverty threshold. If the individuals' income with respect to their family structure falls on the poverty threshold, it takes the value of 100. For example, if a person's family income is $20,000 and the poverty threshold for such a person is $13,861, then the value of poverty for that individual is $20,000/$13,861 * 100 percent, or 144. Individuals whose family income is more than five times the appropriate poverty threshold receive a poverty value of 501. In this analysis, we will treat this variable as categorical variable. Thus, if the individual is on the appropriate threshold or below it, he will be assigned to 0 and if his poverty value is more than 100, he will be assigned to 1.

English ability is another outcome of immigrant workers that we are interested in. This variable is recorded under 5 categories which include does not speak, does not speak well, speak well, speak very well, and native. We will again treat this variable as a categorical variable through this paper. If the individual does not speak English or does not speak well, he will be assigned to 0. If he is native or speaks well or very well, he will be assigned to 1. We also generated an adjusted person weight which allows us to treat each cross section equally-weighted. The mean of the adjusted person weigh for each cross section is 1. This generated person weight is used through this research to to treat data sets of different years equally.

For all matched data sets, namely the main data set, the supplement data set and the final data set, we paid a special attention to the number of observations in each cell that is used to create mean values. Besides, the number of clusters is large enough for each combined data set.

4. DESCRIPTIVE STATISTICS

In this chapter, we will provide information about the number of immigrants and skill level distributions of immigrants across major visa categories with respect to immigrant characteristics based on the main, supplement and final data sets.

4.1. Immigration Policy Implications

Figure 1 presents the number of immigrants who joined the U.S society for each successive year from 1972 to 2000 which shows an increasing trend in the number of immigrants over time. This fact strengthens the importance of investigating the labor market outcomes of immigrant workers. On the other hand, Figure 2 presents the the numbers after imposing the restrictions that are mentioned in the Data section. Despite minor dissimilarities, the general trend is highly correlated with Figure 1. In other words, all the restrictions that we imposed on the data sets, have almost no impact on the representativeness of the restricted data sets on immigrant population. Although the number of observations change significantly, restricted data set replicates the changes in size of immigration flow. At this point one may still claim that the representativeness of the restricted data set is still questionable since the explained relationship between Figure 1 and Figure 2 is only about number of admitted immigrants. In other words, it does not give any information regarding visa composition distribution change over time. To address this reasonable question, we plot proportion of immigrants' visa categories without imposing any restrictions in Figure 3. Figure 4 plots the same graph after imposing aforementioned restrictions. There is significant overlap in trends in Figure 3 and Figure 4 that supports the representativeness of restricted data.

There are significant spikes that appear in Figure 2 in terms of the number of admitted immigrants. These spikes overlap with major immigration policy changes which was brought into force in the U.S. The first significant rise starts in 1976 and lasts until 1978 which can be attributed to "The Immigration and Nationality Act Amendments of 1976". According to Fragomen (1977), the main aim of this act was to make adjustment of visa status feasible for Western Hemisphere immigrants on an equal basis with Eastern Hemisphere immigrants. At the same time, this period was also known for massive refugee immigration from Vietnam. Vietnamese refugees' arrival has both increased the number of accepted people and the ratio of refugees with respect to family and employment related immigrants which can be observed in Figure 4. In 1978 the same law was further extended to establish a worldwide annual ceiling and a uniform preference system that would be applied to every country in the same way. Until 1980, the rise in the number of immigrants has reversed and the number of admitted immigrants fell considerably.

Then, Refugee Act of 1980 came into effect which not only concerns refugees but also impose some restrictions regarding the whole population of immigrants leading to significant changes in terms of number of admitted immigrants. On one hand it provides uniform opportunities to all refugees and increase the established quota to 50.000 from 17.400 for refugees, on the other hand it imposes a quota to the total number of accepted immigrants. This caused a change in visa composition with a lag and increased the fraction of refugees and decreased family related visa's fraction which can again be observed in Figure 4. It is also worth noting that Mariel Boatlift happened during these years.

Immigration Reform and Control Act of 1986 established amnesty for undocumented immigrants and hiring undocumented immigrants is classified as crime. Arriving at 1990, the immigration act relaxed the quota that is imposed on the number of accepted immigrants for each year. The new quota is set to 700.000 which increased the number of visas by 40% for the following years (Leiden and Neal, 1990). Family based visa categories were still dominant after this new act came into effect, yet the most striking outcome of this act was doubling the number of immigrants accepted through employment related visa categories. Until this point, both the number and the ratio of employment related immigrants have been fluctuating in a very narrow corridor, yet with this act not only the number of employment related immigrants is doubled, but also its fraction has improved significantly among visa categories. These changes can be observed in Figure 2 and Figure 4.

Then Clinton Era started in 1994 leading to immigration policy changes in the following years. Immigration and Nationality Technical Corrections Act and Immigration Enforcement Improvements Act of 1995 imposed harsher policies for both existing and prospective immigrants. The main purpose of these acts was to aggressively secure the borders, speed the deportation of illegal aliens, and better enforce the law prohibiting the employment of illegal aliens. In 1995, Clinton makes the following statements which elicit his motivations and its policy implications:

“All Americans, not only in the States most heavily affected but in every place in this country, are rightly disturbed by the large numbers of illegal aliens entering our country. The jobs they hold might otherwise be held by citizens or legal immigrants. The public service they use impose burdens on our taxpayers. That's why our administration has moved aggressively to secure our borders more by hiring a record number of new border guards, by deporting twice as many criminal aliens as ever before, by cracking down on illegal hiring, by barring welfare benefits to illegal aliens. In the budget we will present to you, we will try to do more to speed the deportation of illegal aliens who are arrested for crimes, to better identify illegal aliens in the workplace as recommended by the commission headed by former Congresswoman Barbara Jordan. We are a nation of immigrants. But we are also a nation of laws. It is wrong and ultimately self-defeating for a nation of immigrants to permit the kind of abuse of our immigration laws we have seen in recent years, and we must do more to stop it.”

As a result, deportation of immigrants has increased tremendously for the following years mostly due to a broader definition of crime that put immigrants’ visas legitimacy in danger. Therefore, more people became eligible for deportation. For instance, the number of deported Mexican immigrants increased from 50.000 to 150.000 in two years starting from 1995 (Lind, 2016). Besides, becoming a legal immigrant for existing unauthorized immigrants has become more difficult during this period. Thus, the number of both existing and admitted immigrants has decreased significantly which can again be observed on Figure 2.

Figure 4 reflects the distribution of admitted immigrants across three visa categories, namely family related, employment related and refugee visa categories. Since we mainly focus on the labor market outcomes and skill distributions of immigrant workers throughout this paper, this graph deserves special attention. As the figure indicates, the U.S. immigration policy relies heavily on family related categories rather than the employment visa category. The trend reveals that the ratio of family related immigrants fluctuates in a narrow corridor over time; however, refugees lose significance over time and their ratio with respect to other visa categories decreases significantly for more recent years which again is related to policy changes in the U.S. immigration policy. An opposite pattern is observed for employment related visa categories after 1990 mostly due to the 1990 Immigration Act through which employment related visa categories gained significance.

These policy changes have been very influential on the number of both admitted and existing immigrants and their composition with respect to their visa categories. Since one of the main aims of this paper is to identify immigrant's contribution to the U.S. labor market, it is essential to demonstrate descriptively that immigration policy shapes both the number of admitted immigrants and the visa category ratio. In the following section, we will claim that these changes in both the number admitted immigrants and the composition of their visa categories, determine immigrants' skill and age distribution that matter for labor market outcomes.

4.2. Skill and Age Levels

Figure 5 presents the distribution of gender across immigrant workers over time. This figure, which is generated by the main data set, indicates that the number of admitted immigrant follows a similar pattern so that the graphs overlap heavily for both genders from 1972 to 2000. Nevertheless, the number of female immigrants diverges considerably starting from 1989 which deserves to be noted.

Figure 6 shows education attainments of immigrants across three specified regions which are Europe, Asia and Mexico. This figure is generated through the main data set. These regions are chosen because they each represent a considerable percentage of U.S. immigrants admitted each year during the period in which the analysis is conducted. At the same time, these countries are not only the main source countries, but also immigrants' characteristics from these countries diverge noticeably from each other.

Europe has been the main source region for a long period, yet it has been losing its significance starting from 1970s and Asian population increases remarkably through this period. Mexico has always been the most significant source country in the U.S. immigration history. Mexican immigrants are usually less qualified in terms of their skill levels, which is measured by immigrants' years of schooling, in comparison with other source countries. However, this fact seems to lose significance over time and Mexican immigrants catch up with Asian immigrants for more recent years according to Figure 6. This increasing trend in educational level is observed for most of the regions which are not presented in this figure.

Since we will be conducting the first set of analysis with alternative data sets, it is worth replicating some of the results with our supplemental data. Figure 7 replicates Figure 6 by using the supplement data. As it can be seen from the Figure 7, even though the average years of schooling for the supplement data set differs significantly from the main data set, trends within each region are similar.

The education variable in the main data set is obtained from Census data sets of all source countries. This average years of schooling variable is then matched with the INS data which contains immigrants' characteristics and demographic information, but lacks years of schooling. In other words, we extract average years of schooling information for each immigrant whose gender is A, occupation is B, birth cohort is C, and who is from country D by pooling their fellow citizens who have the same characteristics A, B, C and D and decided not to migrate to the U.S. but stayed in their home country. Then, we take the average years of schooling from each pool and match this educational information with the immigrant who has those characteristics.

The supplement data follows a similar process, yet uses US Census and ACS data sets which implies that we obtain immigrants' years of schooling, whose characteristics are A, C, and D, from US Censuses and implement this information to immigrants who is observed in the INS data set and whose characteristics are again A, C, and D. Hence, the years of schooling is obtained from the source countries for the main data set, it is, however, extracted from the host country, which is the U.S. in this case, for the supplement data set.

This discrepancy causes the differences in the mean years of schooling values. There are a number of potential explanations to this fact. Firstly, required skills may vary considerably for each country and it is not unexpected that the U.S. requires more qualifications for a given occupation in comparison with the rest of world. Secondly, accepted immigrants may be from the top of the skill distribution of the source countries. Hence, the qualifications of the immigrants' and their counterparts' who stayed in the source country, may differ from each other. Lastly, immigrants may have ended up receiving education after their arrival to the U.S. Thereby, the average mean years of schooling values are different in the main and supplement data sets. Nevertheless, since the trend is more important for our analysis and the trends are similar across data sets, these alternative data sets can be used interchangeably.

Figure 8 presents educational attainments of immigrants by visa category. The first implication of this graph is that the average years of schooling, which is obtained by the main data set, is greater for employment related visa categories. Another fact that deserves attention is that starting from 1990s, the average years of schooling of immigrants tends to increase and this increase is very significant for employment-based visa categories. The same interpretation is valid for Figure 9 which aims to shed some light on the same issue by making use of the supplement data set. The difference in terms of percentage points between family and employment visa categories follows a similar pattern which is shown in Figure 21.

Figure 10 represents immigrants' mean age across regions for the main data set and Figure 11 stands for the same graph generated by the supplement data set. The importance that we attribute to these similarities comes from the fact that the country of origin variables consists of slightly different countries for the main and the supplement data sets. Albeit these differences, both data sets show very similar results. An important outcome of Figure 10 and Figure 11 is that the mean age of immigrants increase for both Mexico and Asia over years, whereas European immigrants' mean age remain almost stable with a slightly negative slope. At this point, it is worth asking whether these differences between regions in terms of mean age of immigrants have any projection on mean age with respect to visa categories.

Figure 12 elicits that the increasing trends by regions has a corresponding projection on visa categories. In other words, mean age increases for both family related and employment related immigrants over time. More importantly, although the mean age follows a similar trend for both visa categories, it diverges significantly from each other starting from 1990. The age gap between visa categories widen for more recent years and this descriptive fact will play a crucial role in the analysis.

4.3. Labor Market Outcomes by Skill Levels

We have been using the main and the supplement data sets until this point to explain the differences in immigrant's characteristics, demographics and educational qualifications. From now on, we will mainly focus on immigrants' labor market outcomes which requires a data set collected after their arrivals. The final data set, which is generated through ACS data, provides a considerable number of variables regarding labor market outcomes of immigrants. These outcomes include earned income, wage income, employment status, labor force participation, poverty, English ability, mobility and so on.

Figure 13 represents the relationship between hourly real total personal earned income and years of schooling by gender of immigrants. Real total personal earned income includes wage earners along with the self-employed immigrants. As years of schooling of immigrant increases, the hourly earned income increases for both genders. Nevertheless, the slope of fitted values is steeper for female immigrants. An important implication of these positive slopes is that the U.S. labor market values educational attainments of immigrants. This responsiveness to skill level of immigrants deserves to be shown descriptively since it is not always the case in this literature. The same pattern is observed in Figure 14 which only takes wage earners into account and drop self-employed immigrants from the sample. This consistency between Figure 13 and Figure 14 provides a stronger motivation for the evaluation of skill levels of immigrant workers.

Earnings related outcomes are only one side of the labor market outcomes of immigrants. On the other side of the coin, there is employment status and labor force participation. Figure 15 shows usual hours worked for both genders. The trend has a negative slope for both genders which means the number of hours worked in a week has decreased with recent immigrant arrivals in the final data set. Another fact is the gap in terms of hours worked between male and female immigrants which is not unexpected and representative of the population.

Figure 16 stands for labor market participation of both genders which has a positive slope, i.e. the labor force participation rate increases over time. There is a significant kink for both sex which starts in 1994 and the resulting level difference survives afterwards. This jump and the following difference correspond well with

Clinton era which not only concerns new arrivals, but also existing immigrants by increased number of deportations. Hence, the increased rate of labor market participation matches up with changes in immigration policy.

At this point, we need to clarify a point which concerns Figure 15 and Figure 16. As explained in data section we observe immigrants' labor market outcomes who arrived in 1972 in 2000 for the first time and take the average value of their outcome for the following 17 years. However, the immigrant who arrived in 2000 is observed starting from 2006 until 2017. Thus, the average value for the immigrant who arrived in 1972 may differ from the average value of immigrant's labor market outcome who arrived in 2000 partly due to the number of years spent in the U.S. This fact requires attention in descriptive statistics, however, will be accounted for in the regression analysis.

Figure 17 presents the relationship between labor force participation rate and years of schooling for both sexes. The slope of fitted lines are positive for both sexes and it is steeper for male immigrants. In other words, as years of schooling increases, labor force participation rate of immigrant workers increases, and this increase is larger for male immigrants. Consistently, Figure 18 shows the same relationship for employment level of immigrant workers. A similar trend is observed for both the sign and the magnitude of fitted values slopes as expected. So, as the educational level of immigrant workers rises, their employability increases for both sexes, and it increases faster for male immigrants.

Figure 19 shows the relationship between mobility and skill level of immigrants. An immigrant is considered as mobile if he moved within state or between states. İmmigrants who were abroad last year are dropped from the sample. As the years of schooling of immigrants increase, ratio of mobile immigrants increases for both sexes. A reverse relation is observed for the ratio of immigrants in poverty. As the years of schooling increases, the likelihood that the immigrant is considered as poor decreases for both sexes which can be observed on Figure 20.

Thus, these descriptive figures provide a strong intuition for the outcomes of analysis. In the following section, we will analyze whether our econometric specifications yield consistent results with our intuitions.

5. SKILL DIFFERENTIALS AND RESULTING OUTCOMES

In this section, we first aim to analyze skill differences across immigrant groups with respect to their visa category. Given that the main selection mechanism in the U.S. is distributed across two main visa categories, which are family and employment visa category, it is crucial to understand how much the visa composition causes skill differentials across immigrant groups. Then, we will be concerned about the labor market reflections of these skill differentials.

5.1. Determinants of Skill Differentials

The skill distribution of immigrant workers may be determined by multiple channels. These channels are changes in visa compositions as well as in country compositions. The U.S. may decide to accept more immigrants from the U.K for a given year whose skill levels are relatively higher in comparison with Mexico. Assume that the U.S. decides to accept more immigrants from Mexico for another year who are obviously less qualified in terms of their skill levels. Thus, the differences in terms of immigrants' skill levels according to their year of arrival may be caused by the skill differences by source countries. We will call this effect as the country composition effect.

The alternative mechanism through which skill level of immigrants may be determined is caused by the selection criteria. Figure 8 and Figure 9 descriptively show that an immigrant from employment visa category is more skilled during the entire period than family visa category. Assume that the U.S. decides to accept more immigrants from employment category for a given year and accept more immigrants from family visa category for another year. Assume also that everything else is the same for these years including country composition of immigrants. Under these circumstances, the differences in skill levels for these given years are generated through the change in the weight of visa categories. We will call this effect visa composition effect. Hence, skill differentials among immigrants are derived by visa and country compositions.

Borjas (1993) states that “During the 1960s, about 40 percent of immigrants entering the United States originated in Europe. This had declined to 17 percent by the 1970s. In contrast, only 12.8 percent of immigrants in the 1960s originated in Asian countries, and this tripled to 37.2 percent by the 1970s.” On the other hand, Figure 4 indicates that visa composition of immigrant pool changes significantly over time. At this point, it is crucial to decompose visa composition and country composition effects since we want to understand to what extent visa composition shapes skill differentials among immigrants.

Blinder-Oaxaca decomposition (1973) approach is used to identify the effect of both visa and country composition effects on average years of schooling. Table 1 reports region -in the first column- and country -in the second column- level decomposition outputs for years of schooling by using the main data set. On the upper panel mean predictions by groups are stated. Prediction 1 stands for employment visa category and prediction 2 is for family visa category. Difference states the differences between these two categories. In other words, the average years of schooling for immigrants whose visa category is employment is 11.15, whereas the mean years of schooling family-based immigrants is 9.03. The difference in the mean years of schooling for these two groups is 2.12. In the second panel of the same table, the difference between these groups is decomposed into three parts which are endowments, coefficients, and interaction.

The coefficient of endowments represents region composition effect, i.e. if the regional composition of family visa category were the same as their counterpart, which is the employment category in this case, their years of schooling would be .21 years higher. Furthermore, the coefficient of coefficients reflects visa composition effect, i.e. if immigrants whose visa category is family were selected under employment visa category keeping the region composition fixed, their years of schooling would be 1.76 years higher. The interaction shows the simultaneous effect of differences in endowments and coefficients.

These results are obtained when we classify source countries by broad regions[1]. It is worth further investigating these differences using individual source countries. Column 2 shows country level decomposition results for years of schooling. The average years of schooling for both employment and family visa categories and their differences remain the same since we use the same data set, yet the coefficient of endowments and coefficients changes slightly. If the country composition of family visa category were the same as employment visa category, their years of schooling would be .54 years higher. In addition, if immigrants whose visa category is family related visa were selected under employment visa category keeping the region composition fixed, their years of schooling would be 1.49 years higher. Thus, both analysis indicate that employment related visa category yields more skilled immigrant flow by choosing more skilled immigrants from a given region or country rather than changing the origin composition. In other words, visa composition effect is more dominant than country composition effect for both regional and country level analysis for the main data set.

Although country level analysis produces consistent outcomes with regional level analysis, we want to further check the robustness of our results. Thereby, we conduct the same analysis with the supplement data set. Table 2 reports region -in the first column- and country -in the second column- level decomposition outputs for years of schooling by using the supplement data set. The average years of schooling for immigrants whose visa category is employment is 14.81, whereas the mean years of schooling family-based immigrants is 12.64. The difference in the mean years of schooling for these two groups is 2.16. The mean years of schooling for the supplement data set is higher than the main data as expected. The potential explanations for the differences in mean value across data sets is already discussed in descriptive statistics section.

The coefficient of endowments again reflects country composition effect which is .79, i.e. if the regional composition of family visa category were the same as employment category, their years of schooling would be .79 years higher. The estimated values in coefficients reflects visa composition effect which is 1.22, i.e. if immigrants whose visa category is family were selected under employment visa category keeping the region composition fixed, their years of schooling would be 1.22 years higher.

[1] North America, South America, Mexico, Europe, Middle East, Asia, Africa, Oceania.

Column 2 conducts the same analysis in country level. If the country composition of family visa category were the same as employment visa category, their years of schooling would be 1.16 years higher. In addition, if immigrants whose visa category is family related visa were selected under employment visa category keeping the region composition fixed, their years of schooling would be .94 years higher.

The analysis is conducted for years of schooling value of immigrants, yet the determinants of their potential contribution to the U.S. labor market is not determined only by their education level, but also their age. Age implies the duration of potential contribution of immigrant workers and as one might infer from the context, younger immigrants has potential to contribute to labor market longer. As Figure 12 indicates, which is representative for both the main and the supplement data sets, the age gap between visa categories widens for more recent years. Thus, immigrants with employment visa are not only more educated, but also potentially contributes to the labor market for a longer period. However, this descriptive intuition again caused by a mixture of country and visa composition effect which needs to be decomposed.

Table 3 reports region -in the first column- and country -in the second column- level decomposition outputs for age of immigrants using the main data set. The average age for immigrants whose visa category is employment is 37.09, whereas the mean age of family-based immigrants is 38.17. The difference in the mean age of immigrant groups for these two categories is 1.08. The coefficient of endowments again reflects region composition effect, i.e. if the regional composition of family visa category were the same as employment category, their age would be .58 years higher. The estimated value of coefficients reflects visa composition effect, i.e. if immigrants whose visa category is family were selected under employment visa category keeping the region composition fixed, they would be 1.1 years younger.

Column 2 replicates the same analysis through country level investigation by using again the main data set. If the country composition of family visa category were the same as employment category, their age would be .28 years higher and immigrants whose visa category is family were selected under employment visa category keeping the country composition fixed, they would be .75 years younger. Hence, both analyzes shows that visa composition effect is very significant for the age of immigrants.

Table 4 replicate the same decomposition for age by using the supplement data set in region and country level respectively. The average age for immigrants whose visa category is employment is 37.22, whereas the mean years of schooling family-based immigrants is 38.01. The difference in the mean age of immigrant groups for these two categories is .78.

The endowment coefficient reflects that if the regional composition of family visa category were the same as employment category, their age would be .46 years higher. The coefficient estimates show visa composition effect, i.e. if immigrants whose visa category is family were selected under employment visa category keeping the region composition fixed, they would be .83 years younger. Table 8 conduct the same analysis in country level. If the country composition of family visa category were the same as employment category, their age would be .08 years higher and immigrants whose visa category is family were selected under employment visa category keeping the region composition fixed, they would be .51 years younger. Hence, both analyzes demonstrate that visa composition effect is dominant for age of immigrants.

These decompositions show that visa composition effect is generally a more important determinant than country composition effect for both years of schooling and age of immigrants. After establishing this fact, it is worth investigating the resulting labor market outcomes of immigrants. Following subsection addresses this question for a variety of outcomes.

5.2. Labor Market Outcomes

The analysis in this section addresses whether higher skill levels implied by employment visa lead to more favorable labor market outcomes.

Table 7 reflects number of observations, mean, standard deviation, minimum and maximum of related variables, respectively where our data set is restricted to immigrants who arrived over 1972-2000. Log_Earned stands for logarithm of hourly earned income and logarithm of hourly wage income is represented by Log_Wage. Employment represents immigrant’s employment status categorically and LFP is another categorical variable which stands for labor force participation of immigrants. Poverty and English are other categorical variables which shows whether an immigrant is in poverty and whether he speaks English well. Fam_Ratio, Emp_Ratio and Ref_Ratio represents family, employment and refugee visa category fraction which adds up to 1 for each combination of year of immigration, country of birth and sex. Year stands for year of ACS data and Year_Since shows the number of years since migration. Schooling is years of schooling of immigrants, Age_Sq is square of age of immigrants and Marital_St is a categorical variable equal to 1 for married immigrants.

We are interested in labor market outcomes of immigrants as reflected by their earnings, employability, labor force participation, poverty status, as well as, immigrants' English ability. To this end, we first analyze earnings of immigrants which is usually measured by logarithm of their hourly earnings. Table 10 shows multiple regressions regarding logarithm of hourly earned income. It is worth to remember that earned income includes both wage earners and self-employed immigrants. The table presents eight set of results and the econometric specifications for these models are as follows:

Model 1: Log_Earned= $\alpha + \beta_1$ Fam_Ratio + β_2 Emp_Ratio + β_3 Year + ε

Model 2: Log_Earned= $\alpha + \beta_1$ Fam_Ratio + β_2 Emp_Ratio + β_3 Year + β_4 Landing_Cohort + β_5 Year_Since + ε

Model 3: Log_Earned= $\alpha + \beta_1$ Fam_Ratio + β_2 Emp_Ratio + β_3 Year + β_4 Landing_Cohort + β_5 Interaction + ε

Model 4: Log_Earned= $\alpha + \beta_1$ Fam_Ratio + β_2 Emp_Ratio + β_3 Year + β_4 Landing_Cohort + β_5 Interaction + β_6 Schooling + β_7 Age + β_8 Age_Sq + ε

Model 5: Log_Earned= $\alpha + \beta_1$ Fam_Ratio + β_2 Emp_Ratio + β_3 Year + β_4 Landing_Cohort + β_5 Interaction + β_6 Schooling + β_7 Age + β_8 Age_Sq + β_9 English + ε

Model 6: Log_Earned= $\alpha + \beta_1$ Fam_Ratio + β_2 Emp_Ratio + β_3 Year + β_4 Landing_Cohort + β_5 Interaction + β_6 Schooling + β_7 Age + β_8 Age_Sq + β_9 English + β_9 Marital_St + β_9 Female + ε

Model 7: Log_Earned= $\alpha + \beta_1$ Fam_Ratio + β_2 Emp_Ratio + β_3 Year + β_4 Landing_Cohort + β_5 Interaction + β_6 Schooling + β_7 Age + β_8 Age_Sq + β_9 English + β_9 Marital_St + β_9 Female + β_{10} Region + ε

Model 8: Log_Earned= $\alpha + \beta_1$ Fam_Ratio + β_2 Emp_Ratio + β_3 Year + β_4 Landing_Cohort + β_5 Interaction + β_6 Schooling + β_7 Age + β_8 Age_Sq + β_9 English + β_9 Marital_St + β_9 Female + β_{10} Country + ε

where landing cohort represents time of arrival of immigrants which intervaled in 5 years period except 1972-1975. Year refers to the survey year. Interaction is the interaction variable for landing cohort and year since migration. Female represents female dummy which takes the value 1 if the immigrant is female and 0 otherwise, region divides the sample into 8 categories which are South America, North America excluding Mexico, Mexico, Europe Middle East, Asia, Africa, Oceania. Country represents country of birth of immigrants. All the remaining variables are explained above. All of the standard errors are clustered by year, country and sex of immigrants.

We will estimate these specifications also for logarithm of wage income, employment status, labor force participation, and poverty status. We will also estimate models where English ability of immigrants is the dependent variable. In that case we drop Model 5 in which we normally add English ability. Thus, we will end up with 7 models rather than 8 while investigating English ability of immigrants.

First column of Table 8 for log earnings shows that holding a family visa negatively and an employment visa positively affect earnings of immigrants when we only control for year fixed effects. Since the base group is refugees, negative sign for family visa means that family related immigrants earn less than refugees. Coefficients of both family and employment ratios are both economically and statistically highly significant. For example, when employment ratio increases by one sample standard deviation (0.147), the earned income increases by 17%. We will add all the explanatory variables step by step to see whether holding an employment visa loses significance as control for other characteristics.

Model 2 adds landing cohort dummy which is grouped in 5-year periods except 1972-1975 and year since migration as a continuous variable to Model 1. Interestingly, economic significance of both family and employment visa fractions rises after including landing cohort and year since migration. Landing cohort tends to be significant for different cohorts at first glance, but it will lose its significance once we add further explanatory variables to the model. However, year since migration remains statistically significant at 1% level, yet it will lose an important part of its economic significance after adding other explanatory variables.

Model 3 includes family and employment fractions, year fixed effect, landing cohort dummy and its interaction with year since migration. By including this interaction, we allow flexibility in terms of earning profiles slopes. Since the significance of interaction term increases for more recent periods, it worth including the interaction throughout the econometric specifications. It is worth to note that inclusion of interaction neither change visa categories economics significance nor their statistical significance.

Model 4 adds to immigrants' characteristics to Model 3 which are years of schooling, age and square of age. Square of age is added to capture any nonlinear relationship between age and earned income following existing literature. These variables are both economically and statistically very significant. If years of schooling increases by 1, earned income increases by 6.4% and if age of immigrants increase by 1, its reflection on earned income is 1.8%. In the following steps where we include further explanatory variables, neither economical nor statistical significance of these variables change. At this point if we increase respective visa fractions by one standard deviation, immigrants' earned income increases by 12% for employment visa holders and decrease by almost 4% for family visa holders.

Model 5 adds marital status and female dummy to Model 4. These variables are again significant at 1% level, and their economic significance is also considerable. Being a female negatively affects earnings. One standard deviation increase in employment fraction increase earned income by 10% for employment visa holders and decrease by almost 3% for family visa holders.

Model 6 adds English ability dummy to Model 5 which is again very significant both economically and statistically. After this point, in Model 7 we add region fixed effect to the model 6. Region of origin explains an important part of economic significance of the remaining variables, yet the statistical significances are not affected by the region fixed effect. More importantly family visa category changes its sign which means that family visa holders perform better than refugees for earned income outcome at this point of the econometric model, however its economic significance is ignorable. One standard deviation increase in employment fraction increase earned income by 7% for employment visa holders and increase by less than 1% for family visa holders.

We also conducted the same analysis using country level fixed effects in Model 8 by adding country dummy to Model 6. Interestingly, employment fraction keeps its statistical significance at 1% level and its economic significance is still high. If we increase employment fraction from 0 to 1, earned income increase by 22%. In other words, if employment fraction increased by one standard deviation, the earned income increases by 3.3%. Family fraction loses its statistical significance for this detailed analysis.

Therefore, we further claim that holding an employment visa affects earned income of immigrants even in this last specification. We will replicate the same analysis by keeping steps for each model the same and changing only left-hand side of the specification with logarithm of wage income and present the results in Table 9. We will only discuss the outcomes of Model 7 and Model 8 given that statistical significance match almost perfectly with earned income and economic significance, i.e. magnitude of related coefficients only differs slightly. One standard deviation increase in employment fraction increase wage income by again 7% for employment visa holders and increase by again less than 1% for family visa holders in Model 7 of Table 9. If employment fraction increased by one standard deviation, the earned income increases by again 3.3%.

For employment status, labor force participation, poverty, and English, which are categorical variables, we replicate the analysis keeping the right-hand side the same for each consecutive step -except one aforementioned step for English ability-, the results of which are presented in Table 10, Table 11, Table 12, and Table 13, respectively. Even though we observe similar patterns for employment fraction's statistical significance, economic interpretation of these outcomes is different than earning related outcomes because of the categorical variables on the left-hand side. If we increase employment visas' fraction from 0 to 1, employment fraction's coefficient multiplied by 100 will tell us the percentage point change in the probability of employment, labor force participation, poverty, Englisg ability, i.e. the probability that immigrant is employed, in the labor force, is not considered as poor, and speaks English well. Except country level detailed analysis, holding an employment visa is both statistically and economically significant for all outcomes.

Hence, immigrants with employment visa perform much better for all six outcomes which are earned income, wage income, employment status, labor force participation status, poverty status, and English ability. Nonetheless, family visa holder immigrants perform even worse than refugees for some cases.

6. CONCLUSIONS

This paper tries to understand the skill differential of immigrants in the U.S. whose year of immigration is between 1972 and 2000. Our main aim is to understand the mechanism behind skill deferential of immigrants. To this end, we have been mainly focusing on multiple effects which determines skill levels of immigrants, namely country composition effect and visa composition effect. It is crucial to understand which effect is dominant to be able to infer any policy implications. We have been using multiple combinations of INS, IPUMS, US Census and ACS data sets to generate our results.

Descriptively, we presented results that show fractions of visa categories and respective skill levels are related to immigration policies in the U.S. For instance, both employment visa category ratio and skill level of this category increase significantly in comparison with family and refugee categories in 1990s mostly due to newly introduced immigration policies. These changes in skill level of immigrants motivates the analysis of the mechanisms behind it.

Our results obtained from INS-IPUMS combination highlights that visa composition dominantly determines immigrants' skill levels and age for regional and country level analysis. For instance, if immigrants whose visa category is family visa were selected under employment visa category keeping the region composition fixed, their years of schooling would be 1.49 years higher. However, if the country composition of family visa category were the same as employment visa category, their years of schooling would be only .54 years higher. Similarly, if the regional composition of family visa category were the same as employment category, their age would be .58 years higher. Nonetheless, if immigrants whose visa category is family were selected under employment visa category keeping the region composition fixed, they would be 1.1 years younger. We replicated the same analysis by combining INS and US Census data sets to check the robustness of the results and obtained similar outcomes. Thus, the skill deferential between employment and visa categories is mainly related to selectivity of employment visa category rather than the differences in regional compositions.

After establishing the fact that visa composition is a more important determinant of skill differentials between immigrants than regional origin composition, it is worth examining whether this selection yields beneficial labor market outcomes for immigrants.

It is shown that employment visa holders perform much better for all five labor market outcomes which are earned income, wage income, employment status, labor force participation status, and poverty status, as well as, English ability. Earned and wage income levels are significantly larger for employment visa holders, yet family visa holders perform even worse than refugees for most of the analysis. The likelihood that immigrants are unemployed, not in labor force, have poor English skills is much less for employment visa holders. Besides, these outcomes are not only statistically significant, but also their economic significance is high.

This paper provides a fertile ground for inferring policy implications. It is empirically shown that it is more effective to select higher skilled immigrants by rearranging visa composition rather than by changing region of origin composition. It is also shown that employment visa holders perform better even in detailed specifications in terms of their labor market outcomes than family visa category.

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APPENDIX

Figure 1: Number of immigrants for each year without imposing any restrictions.

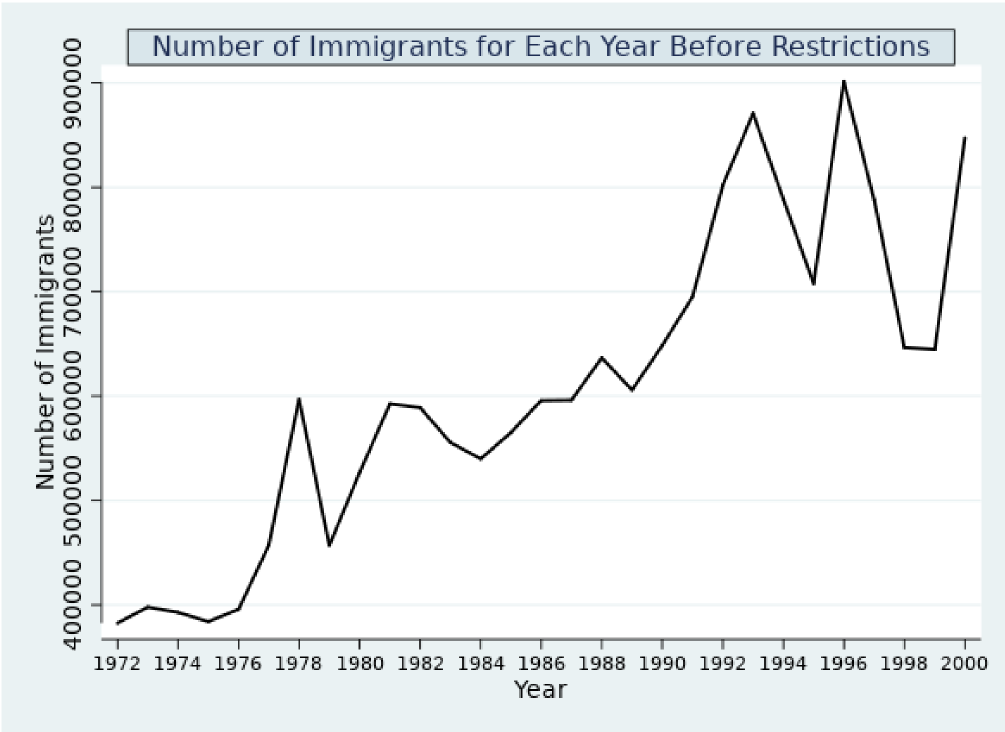

Figure 2: Number of immigrants for each year after restrictions.

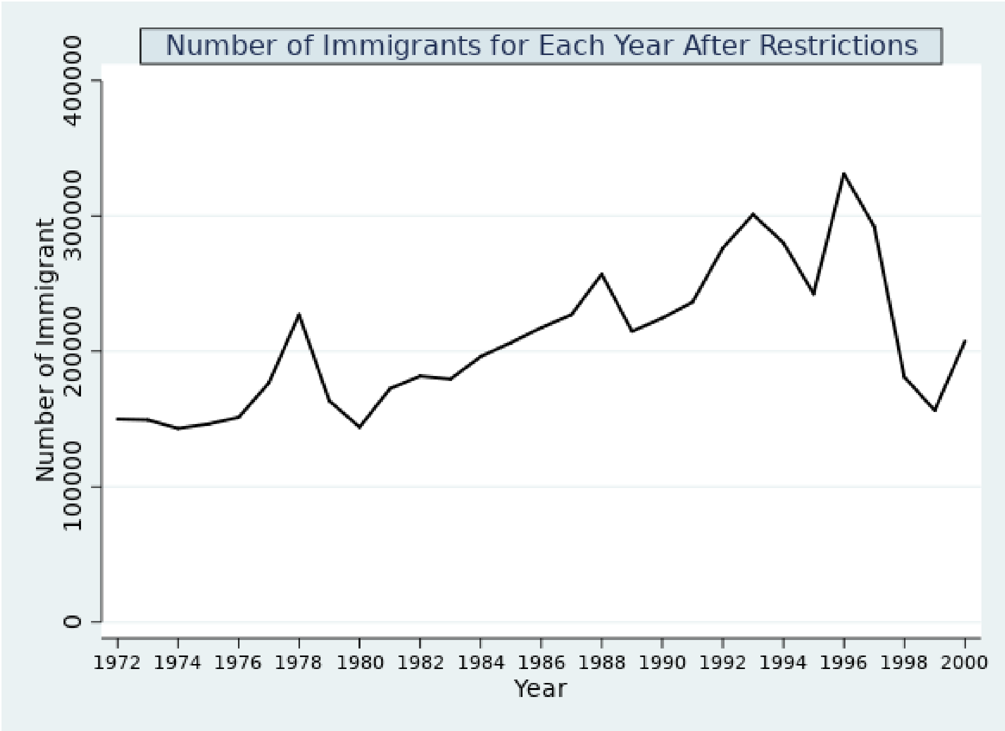

Figure 3: Ratio of immigrants by visa categories before restrictions

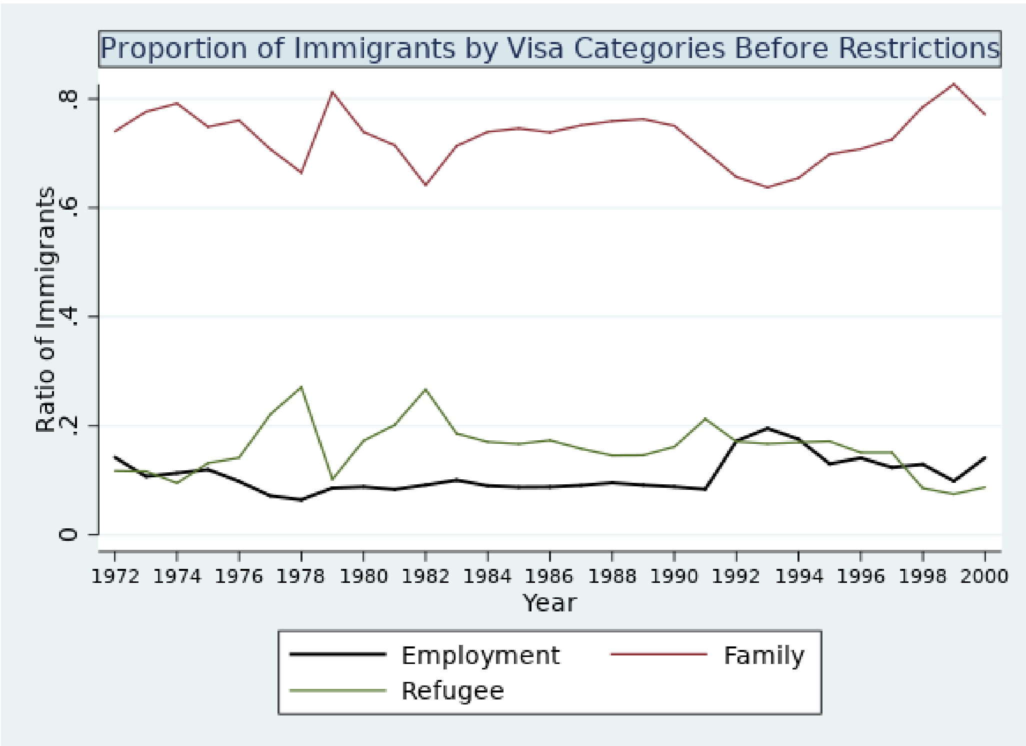

Figure 4: Ratio of immigrants by visa categories after restrictions

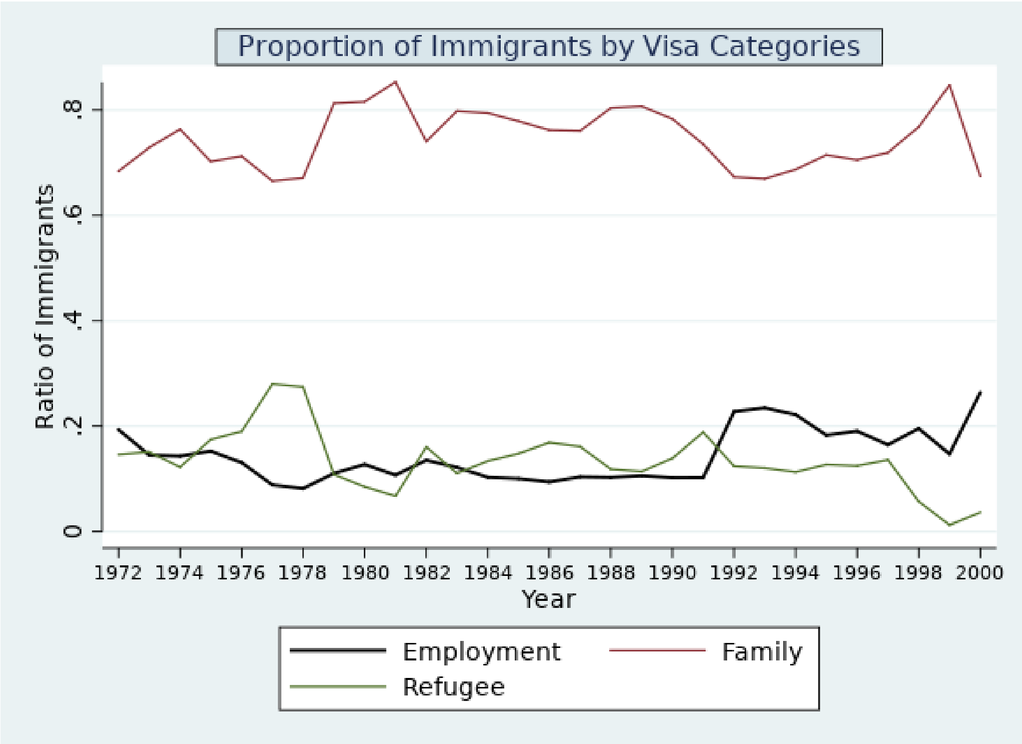

Figure 5: Number of immigrants by gender

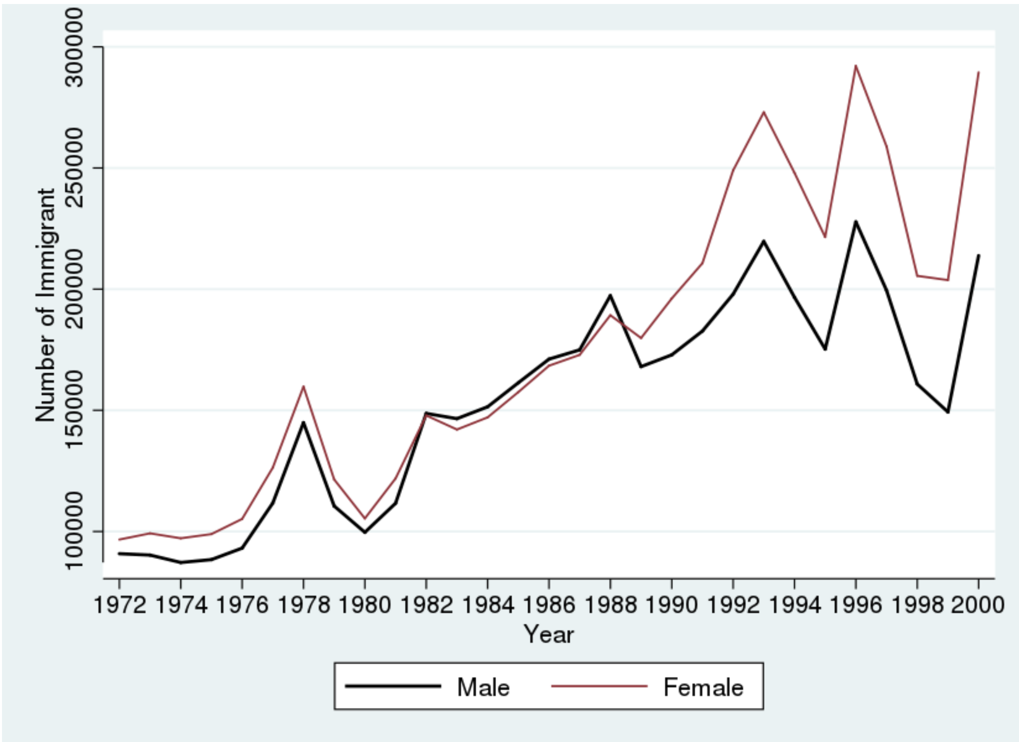

Figure 6: Educational attainments of immigrants across regions for the main data set

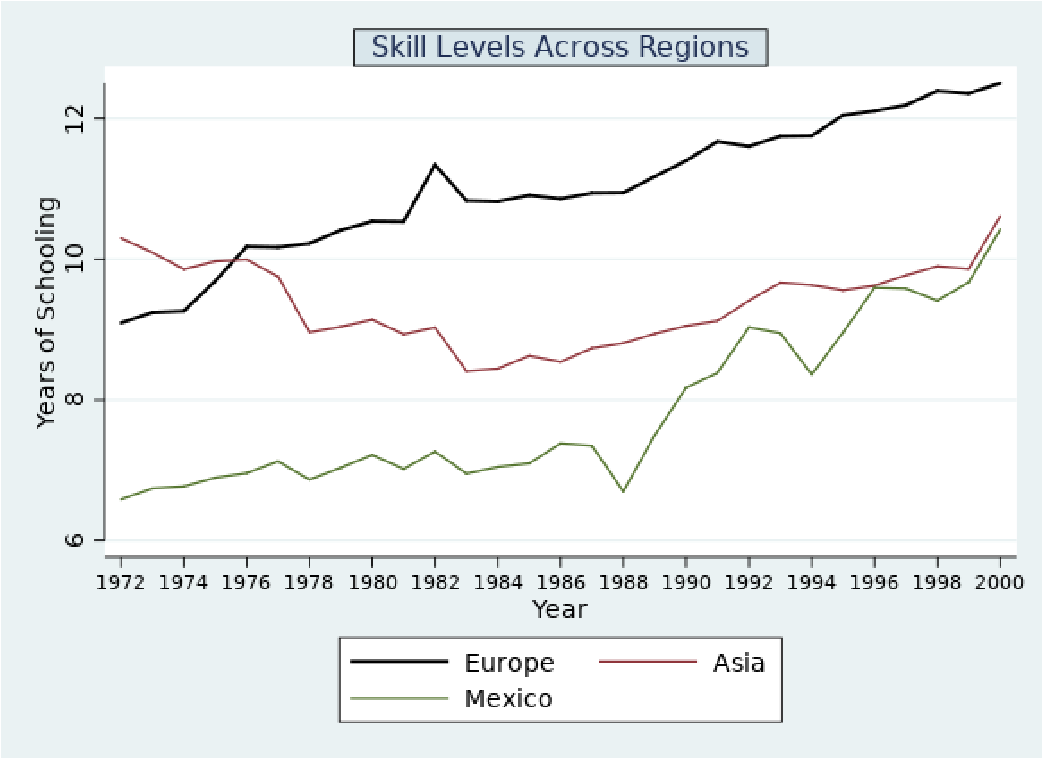

Figure 7: Immigrants' years of schooling across regions for the supplement data set

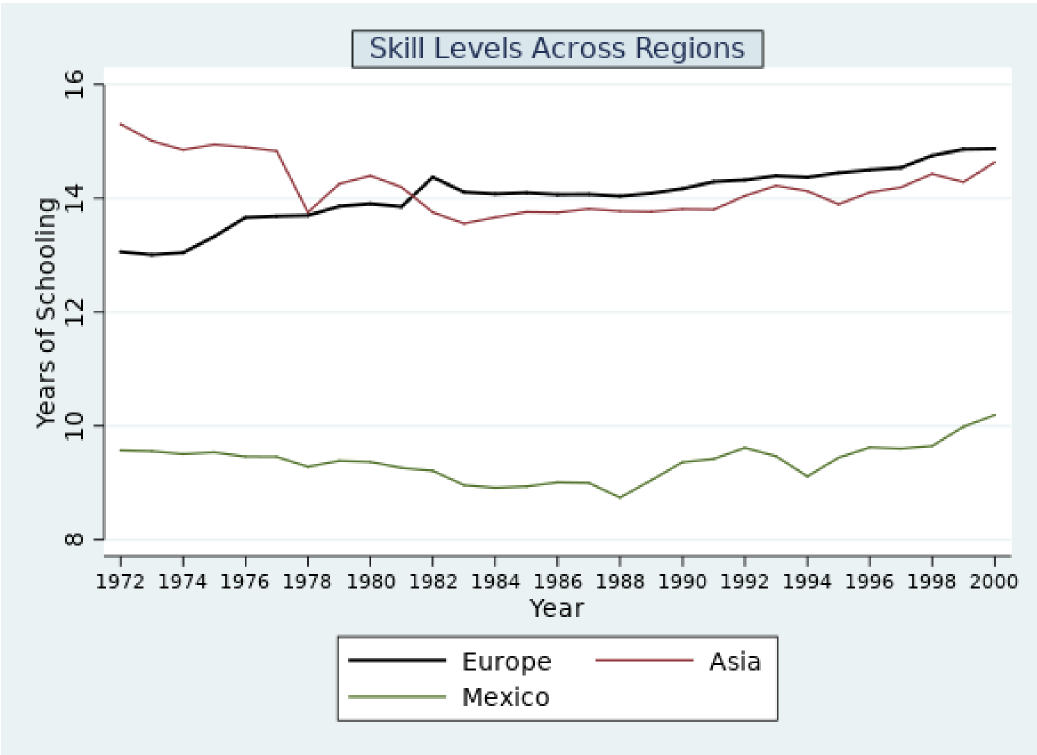

Figure 8: Educational attainments of immigrants by visa category for the main data set

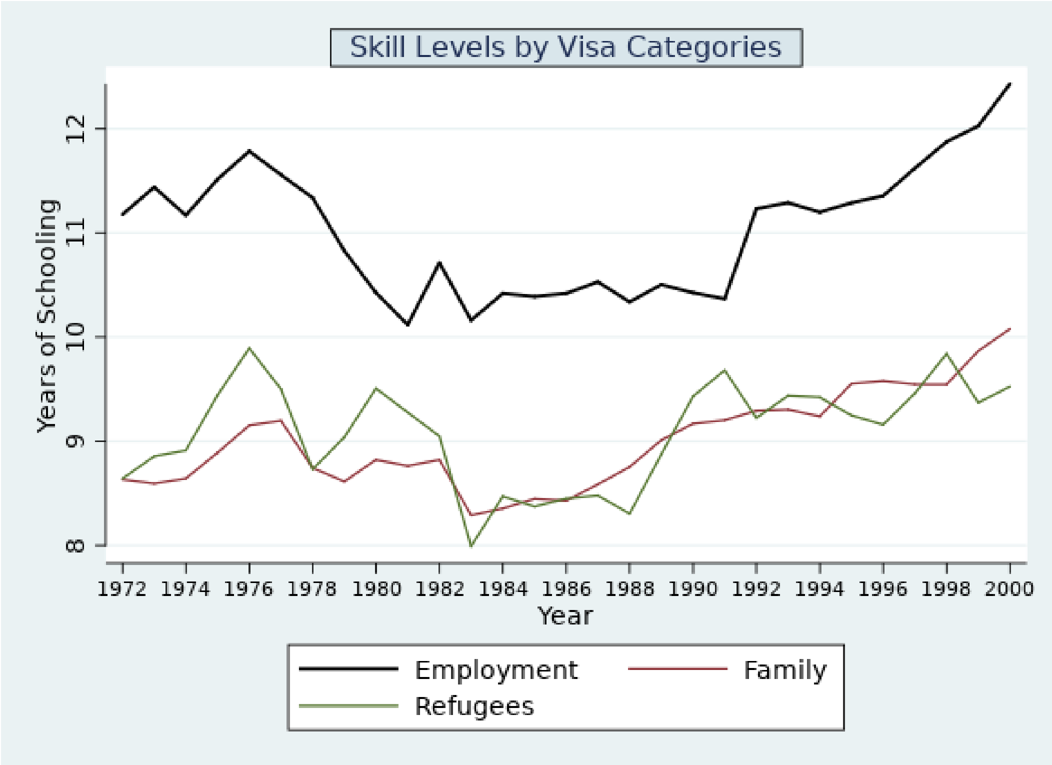

Figure 9: Immigrants' years of schooling by visa category for the supplement data set

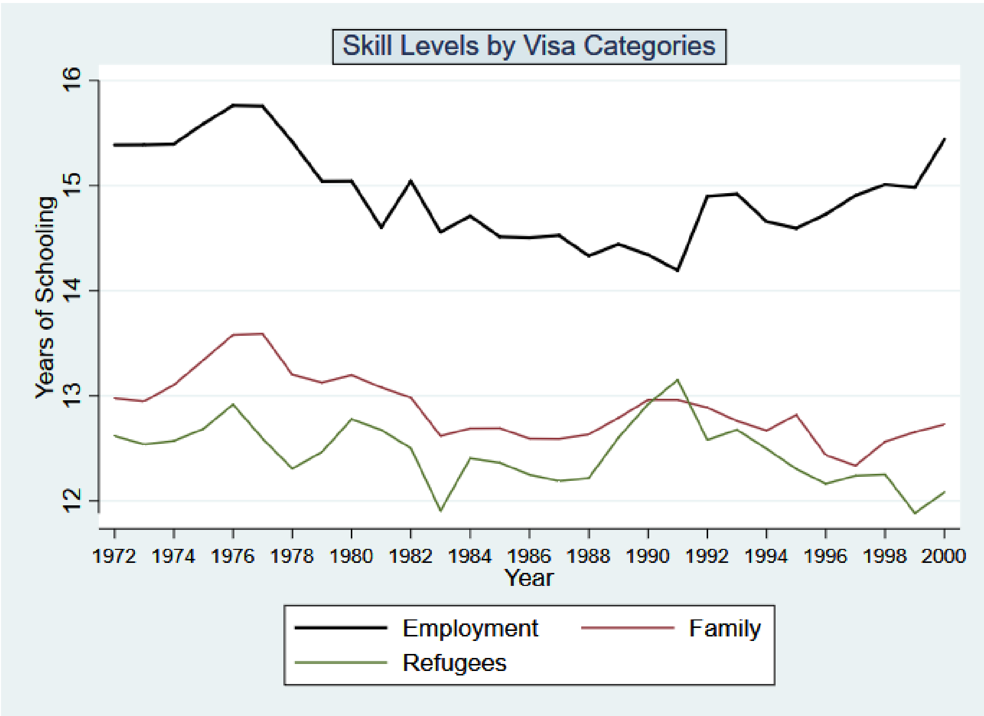

Figure 10: Immigrants' mean age across regions for the main data set

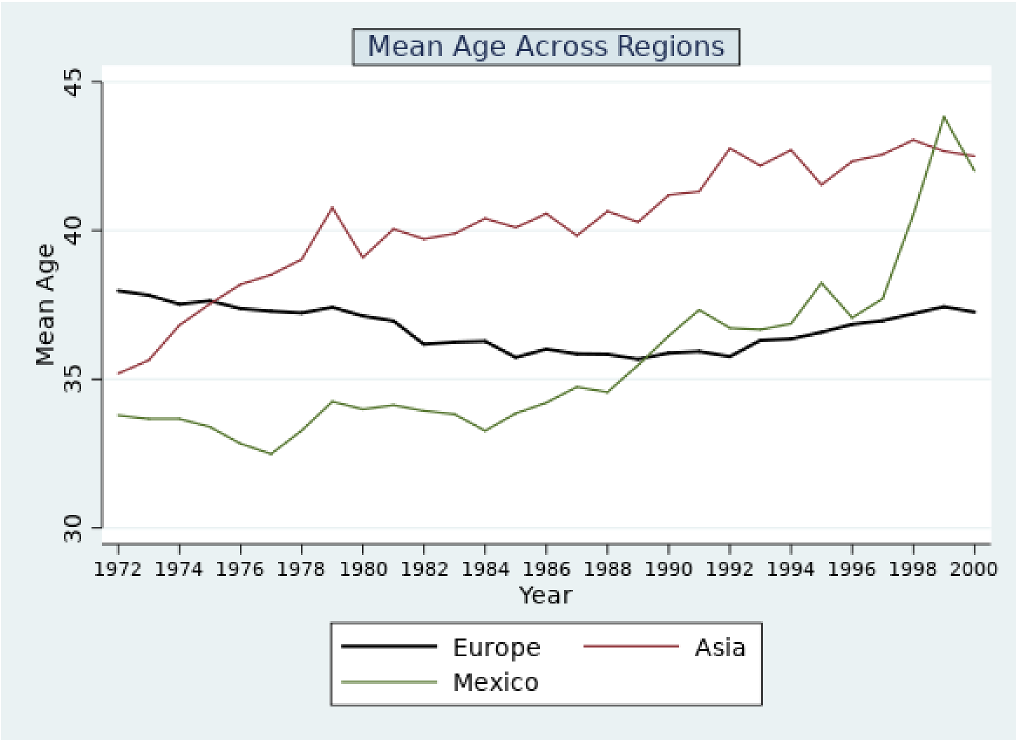

Figure 11: Immigrants' mean age by visa category for the supplement data set

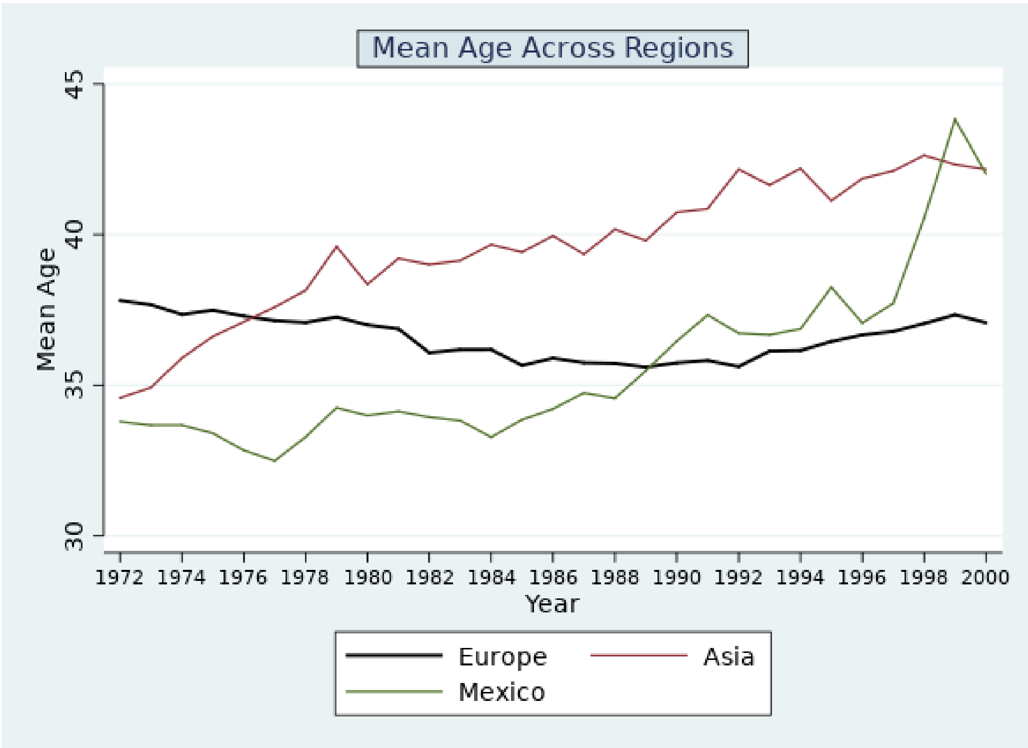

Figure 12: Immigrants' mean age by visa categories

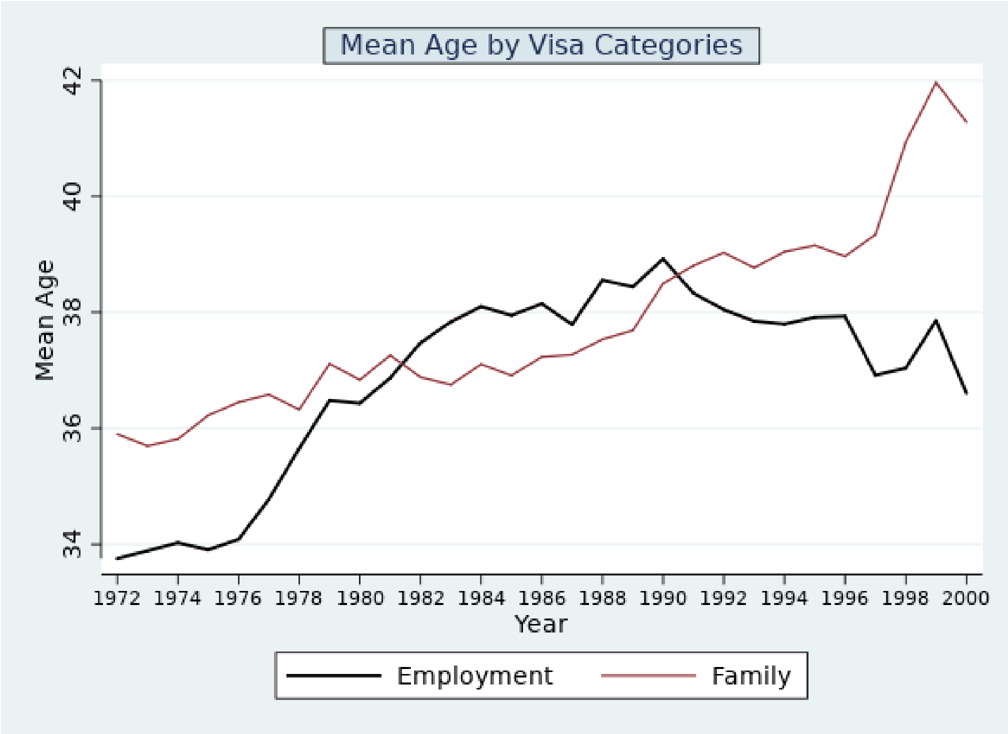

Figure 13: Hourly real total personal earned income vs. years of schooling by sex

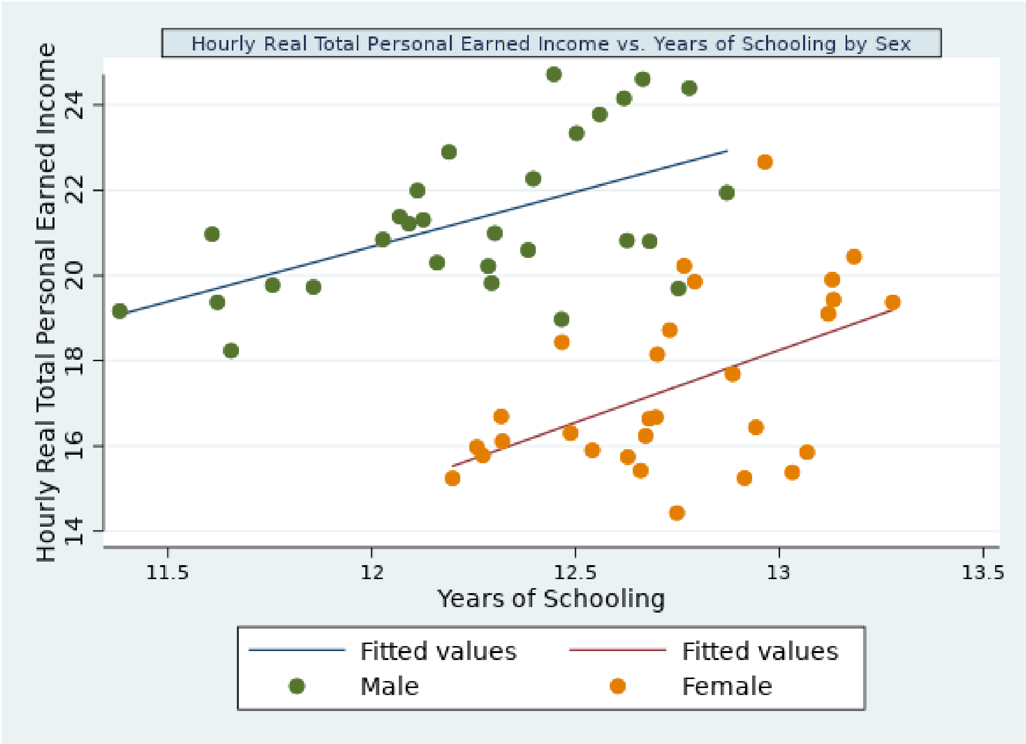

Figure 14: Hourly real wage income vs. years of schooling by sex

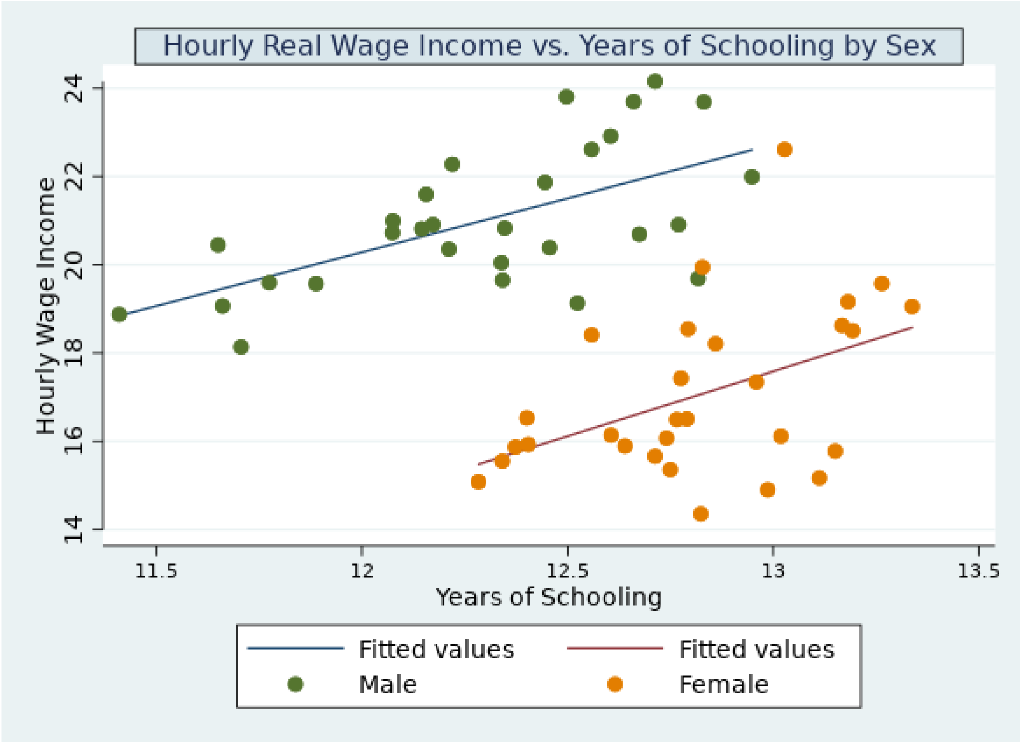

Figure 15: Usual hours worked by sex

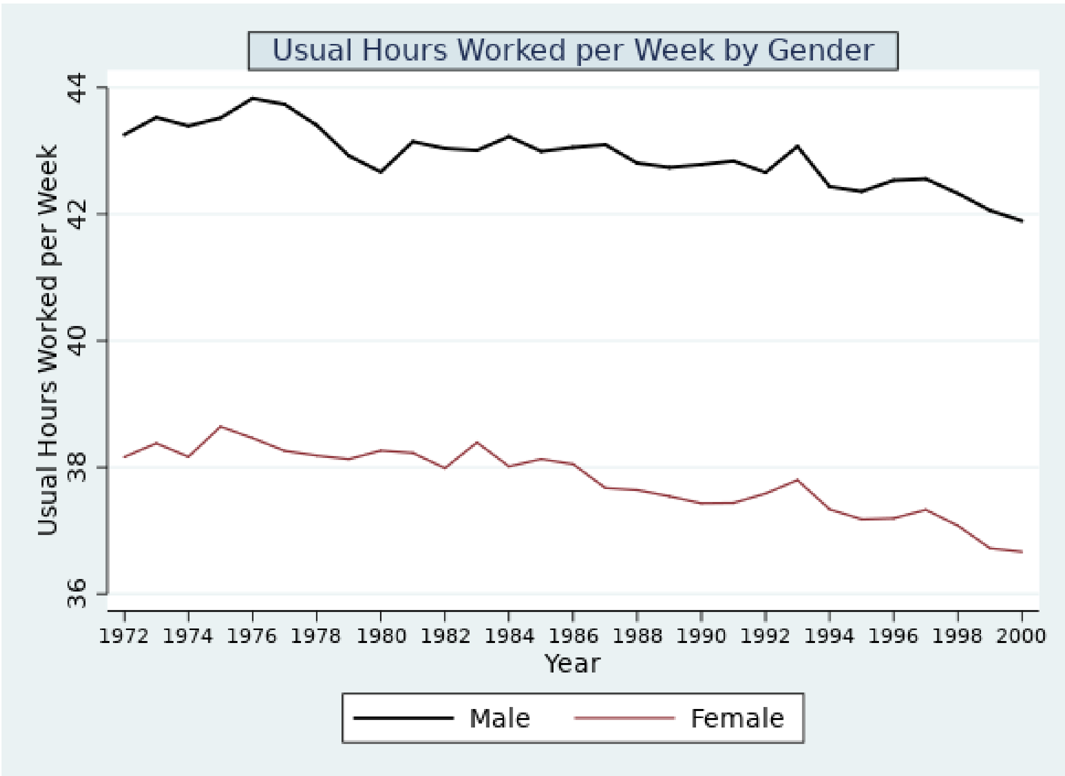

Figure 16: Labor force participation rate by sex

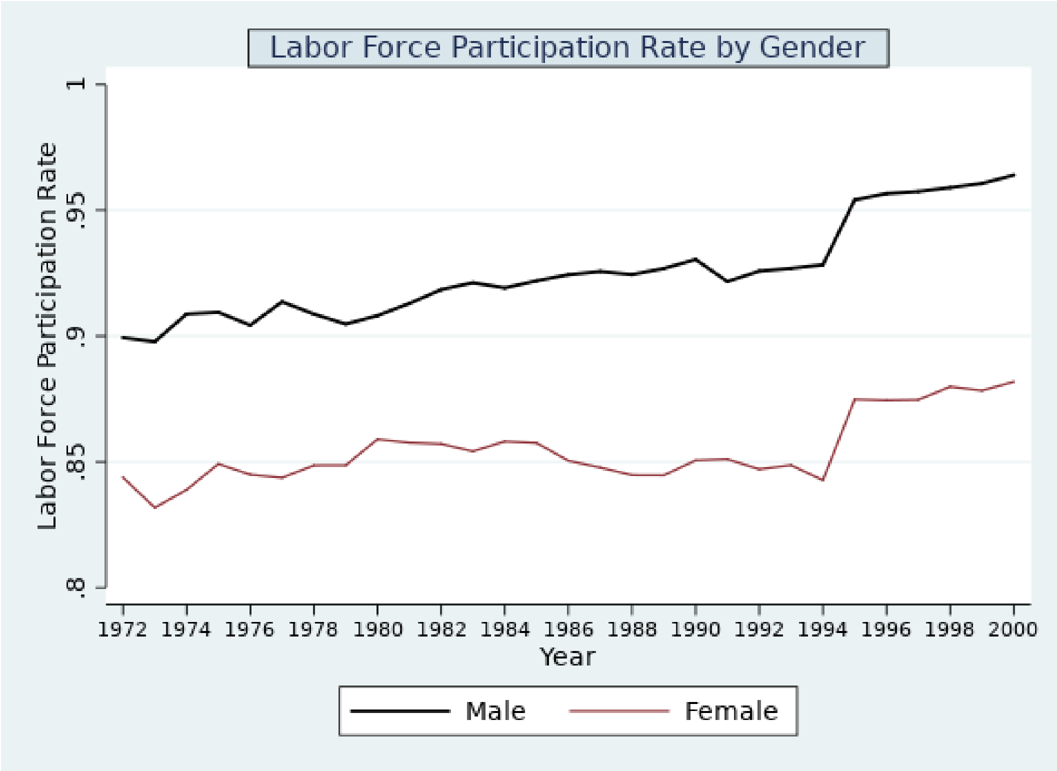

Figure 17: Labor force participation rate vs. years of schooling by sex

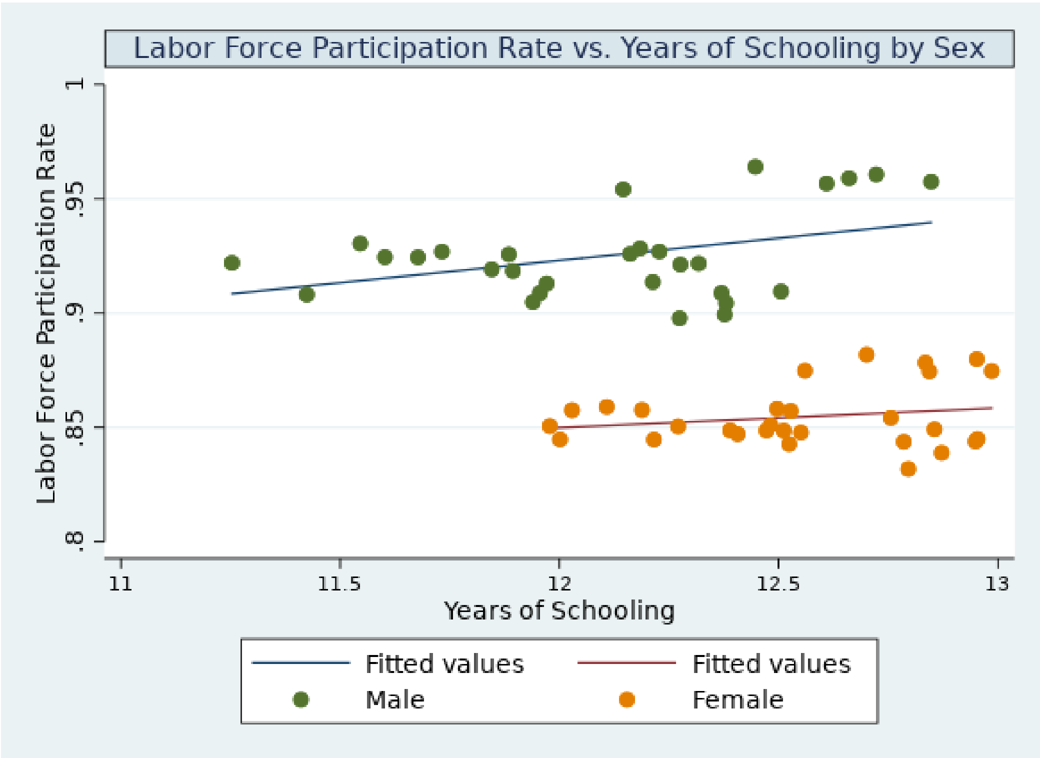

Figure 18: Employment rate vs. years of schooling by sex

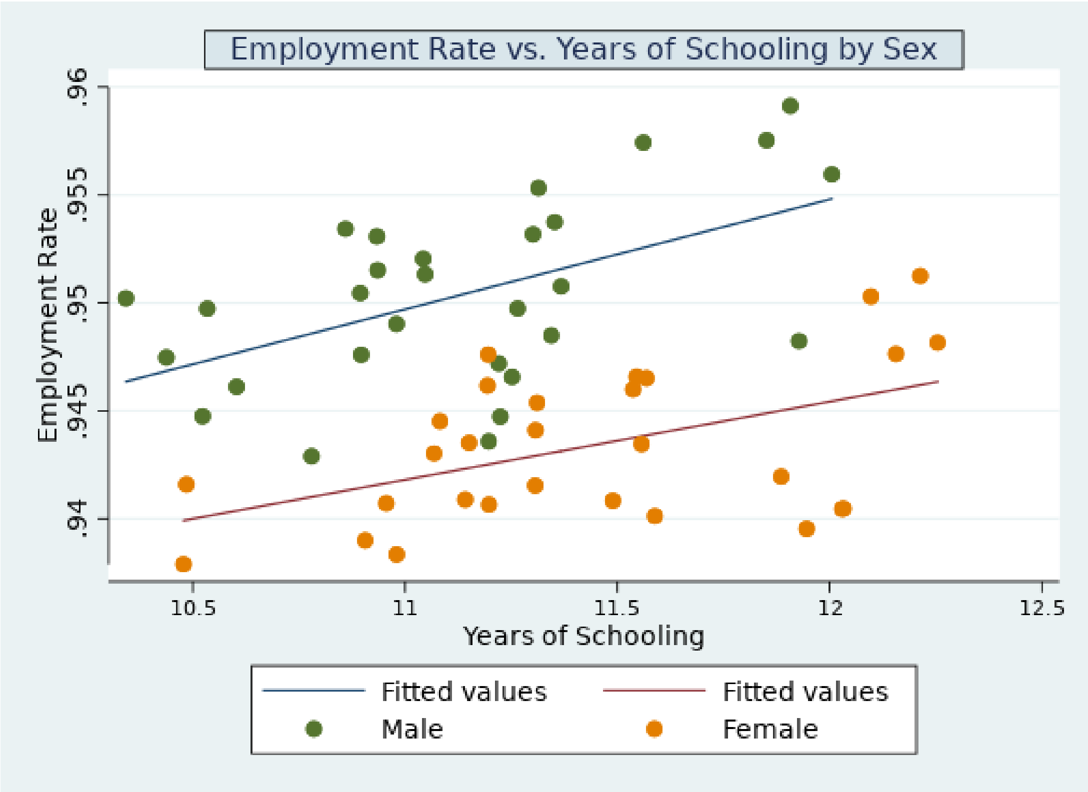

Figure 19: Mobility vs. years of schooling by sex

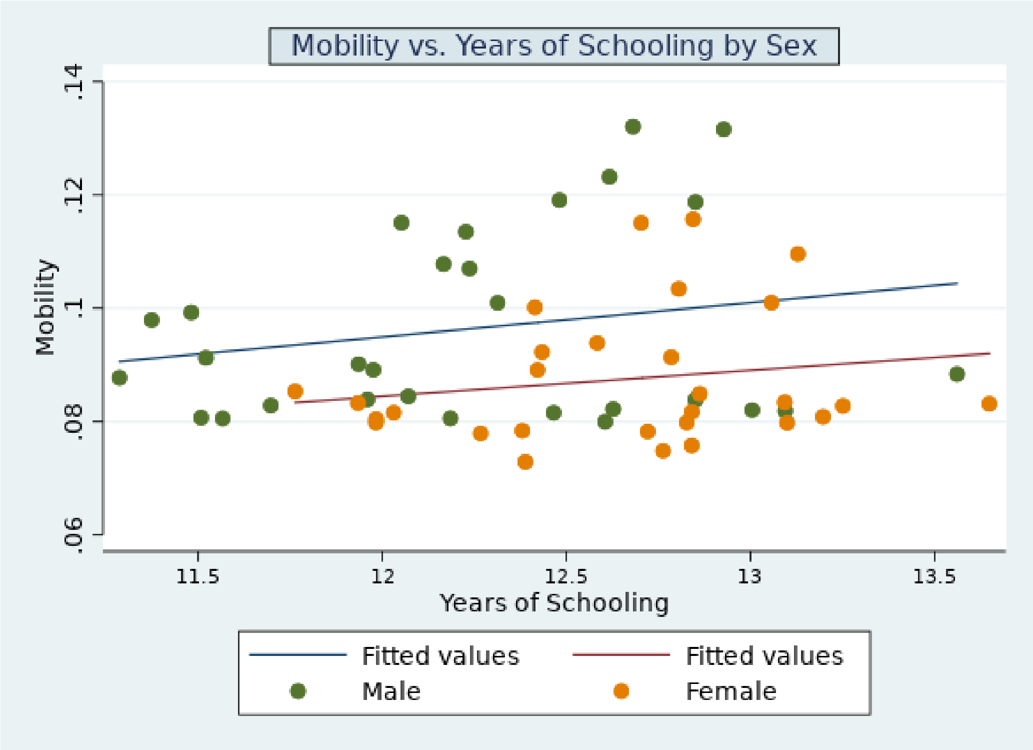

Figure 20: Percentage of immigrants in poverty vs. years of schooling by sex

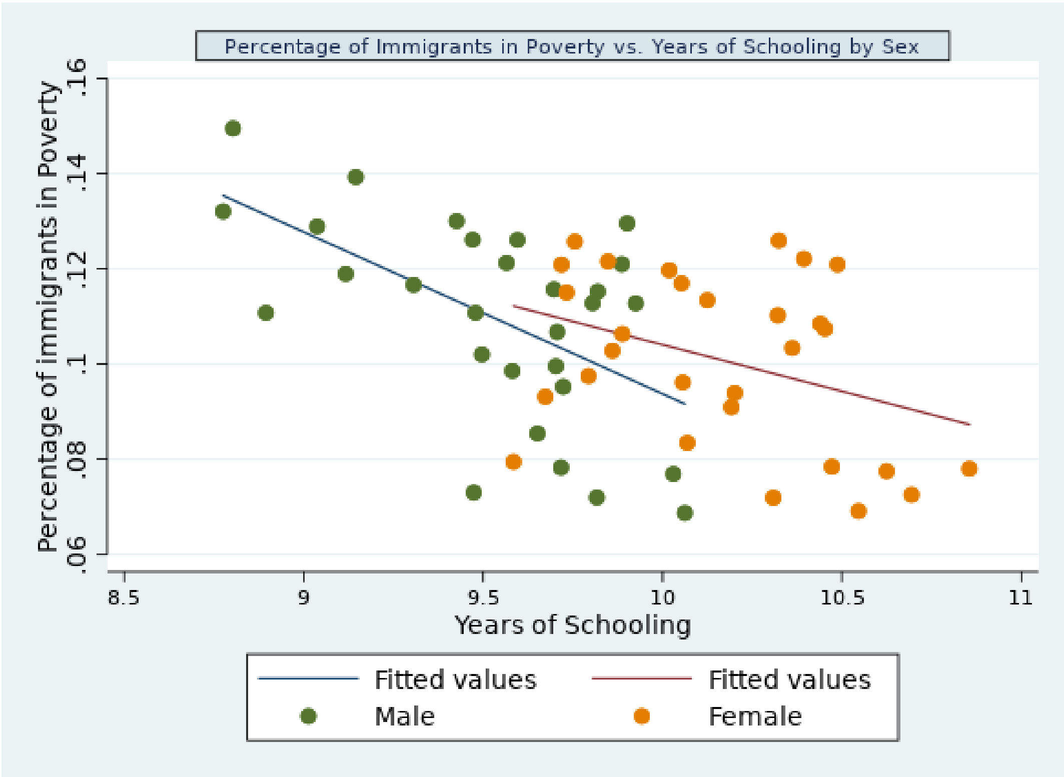

Figure 21: Skill Levels Difference between Employment and Family Categories

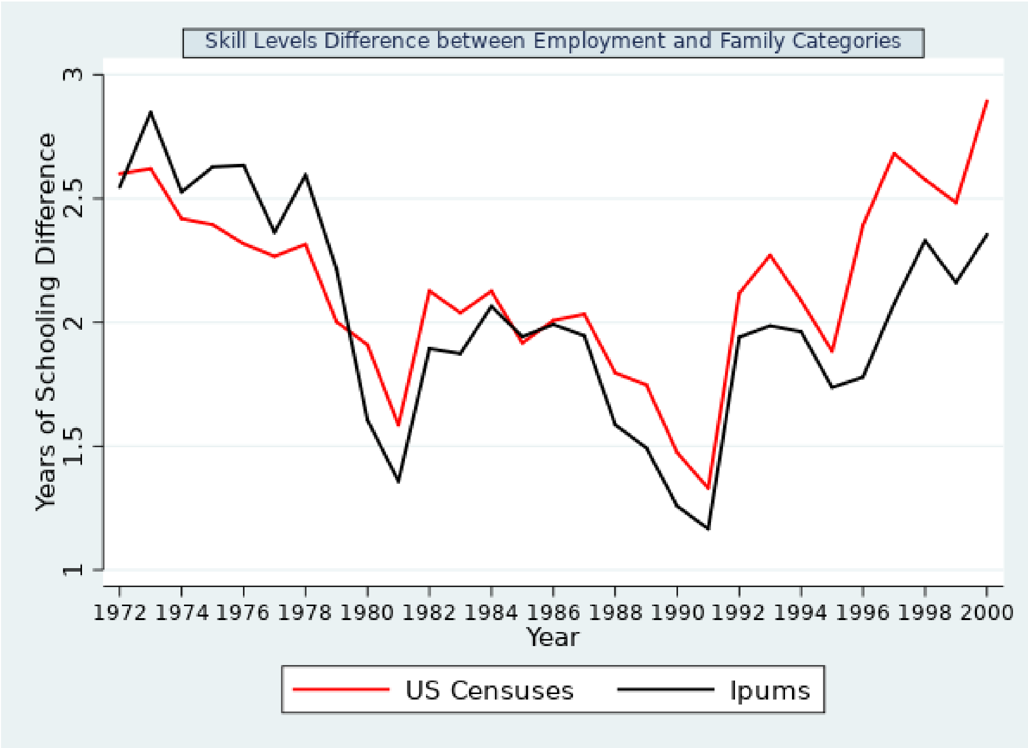

Table 1: Region and Country level Oaxaca decomposition for years of schooling with the main data set.

	Model 1	Model 2
Differential		
Prediction_1	11.15***	11.15***
	(2941.98)	(2941.89)
Prediction_2	9.034***	9.034***
	(5000.60)	(5000.56)
Difference	2.120***	2.120***
	(504.85)	(504.83)
Decomposit~n		
Endowments	0.219***	0.549***
	(179.13)	(214.02)
Coefficients	1.764***	1.492***
	(331.45)	(245.41)
Interaction	0.137***	0.0794***
	(38.24)	(14.83)
N	4217004	4217004

t statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 2: Region and Country level Oaxaca decomposition for years of schooling with the supplement data set.

	Model 3	Model 4
Differential		
Prediction_1	14.81***	14.81***
	(5478.01)	(5477.88)
Prediction_2	12.64***	12.64***
	(9560.89)	(9560.85)
Difference	2.167***	2.167***
	(719.88)	(719.87)
Decomposit~n		
Endowments	0.799***	1.168***
	(518.07)	(571.69)
Coefficients	1.225***	0.964***
	(374.83)	(269.86)
Interaction	0.143***	0.0346***
	(66.80)	(11.27)
N	5003820	5003820

t statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 3: Region and Country level Oaxaca decomposition for age with the main data set.

	Model 5	Model 6
Differential		
Prediction_1	37.09***	37.09***
	(3945.44)	(3945.22)
Prediction_2	38.17***	38.17***
	(6803.47)	(6803.39)
Difference	-1.082***	-1.082***
	(-98.80)	(-98.80)
Decomposit~n		
Endowments	0.583***	0.285***
	(159.40)	(49.38)
Coefficients	-1.109***	-0.759***
	(-81.43)	(-42.67)
Interaction	-0.555***	-0.608***
	(-59.43)	(-38.97)
N	4672786	4672786

t statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 4: Region and Country level Oaxaca decomposition for age with the supplement data

	Model 7	Model 8
Differential		
Prediction_1	37.22***	37.22***
	(4276.28)	(4276.06)
Prediction_2	38.01***	38.01***
	(7251.41)	(7251.33)
Difference	-0.786***	-0.786***
	(-77.31)	(-77.31)
Decomposit~n		
Endowments	0.463***	0.0841***
	(149.20)	(16.25)
Coefficients	-0.837***	-0.515***
	(-66.84)	(-31.76)
Interaction	-0.412***	-0.355***
	(-49.96)	(-25.32)
N	5309449	5309449

t statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 5: Summary statistics for related variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
Log_Earned	1,410,973	2.640624	.7984629	-8.551814	10.73956
Log_Wage	1,398,186	2.625661	.8023788	-7.280639	10.73956
Employment	1,793,034	.9629544	.1888736	0	1
LFP	1,932,938	.9276211	.2591144	0	1
Poverty	1,932,938	.9217978	.2684896	0	1
English	1,932,938	.7594527	.4274159	0	1
Fam_Ratio	1,883,692	.7784027	.2504318	0	1
Emp_Ratio	1,883,692	.130659	.1470904	0	1
Ref_Ratio	1,883,692	.0909382	.2384811	0	1
Year	1,932,938	2007.133	5.736774	2000	2017
Year_Since	1,932,938	20.98865	8.621857	6	45
Schooling	1,932,938	12.47903	4.735512	0	22
Age	1,932,938	44.78679	9.355051	25	65
Age_Sq	1,932,938	2093.374	848.7071	625	4225
Marital_St	1,932,938	.7284926	.4447373	0	1

Table 6: Percentage of Remaining Data.

	Without Restriction	**Year of Immigration**	**Age**	**Occupation**	**Country or Country of Birth**
INS for IPUMS	**1**	**-**	**.55**	**.42**	**.35**
INS for US Censuses	**1**	**-**	**.55**	**.42**	**.4**
US Censuses	**-**	**1**	**.73**	**.62**	**.6**
IPUMS	**1**	**-**			

Table 7: Outcome of regression in which the dependent variable is logarithm of hourly earned income.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Family Fraction	-0.271***	-0.316***	-0.316***	-0.145***	-0.103***	-0.0983***	0.0351***	-0.0210
	(-9.01)	(-11.18)	(-11.22)	(-7.71)	(-7.04)	(-7.44)	(2.81)	(-0.84)
Employment Fraction	1.131***	1.389***	1.391***	0.827***	0.689***	0.628***	0.504***	0.222***
	(20.44)	(24.29)	(24.37)	(19.26)	(19.04)	(18.96)	(16.88)	(6.96)
Landing Cohort=7680		0.127***	0.0443	0.00674	-0.0109	-0.00673	0.00316	-0.0361
		(2.99)	(0.60)	(0.11)	(-0.26)	(-0.17)	(0.08)	(-1.11)
Landing Cohort=8185		0.195***	0.221**	0.0984	0.0666	0.0721*	0.0596	0.00535
		(2.83)	(2.57)	(1.46)	(1.43)	(1.66)	(1.43)	(0.16)
Landing Cohort=8690		0.272***	0.230**	0.0777	0.0569	0.0665	0.0431	-0.0209
		(2.75)	(2.27)	(1.00)	(1.08)	(1.37)	(0.96)	(-0.61)
Landing Cohort=9195		0.245*	0.122	-0.00121	-0.00598	0.00998	0.00261	-0.0514
		(1.84)	(0.91)	(-0.01)	(-0.09)	(0.17)	(0.05)	(-1.34)
Landing Cohort=9600		0.309*	0.154	-0.00704	-0.0160	-0.00154	-0.0202	-0.0747*
		(1.89)	(0.94)	(-0.06)	(-0.21)	(-0.02)	(-0.35)	(-1.71)
Year Since Migration		0.0269***	0.0247***	0.0163***	0.0156***	0.0133***	0.0114***	0.00961***
		(4.07)	(3.79)	(3.62)	(5.16)	(4.96)	(5.28)	(6.09)
Landing Cohort=768~e			0.00233	0.00242	0.00251**	0.00218**	0.00161	0.00192**
			(1.25)	(1.49)	(2.27)	(2.03)	(1.56)	(2.20)
Landing Cohort=818~e			-0.00176	0.000331	0.000850	0.000356	0.000254	0.000857
			(-0.95)	(0.21)	(0.83)	(0.36)	(0.25)	(0.98)
Landing Cohort=869~e			0.000479	0.00233	0.00237**	0.00157	0.00150	0.00198***
			(0.23)	(1.56)	(2.09)	(1.50)	(1.59)	(2.58)
Landing Cohort=919~e			0.00479**	0.00533***	0.00552***	0.00436***	0.00368***	0.00380***
			(2.57)	(3.40)	(4.75)	(3.89)	(3.54)	(4.42)
Landing Cohort=960~e			0.00815***	0.00837***	0.00873***	0.00727***	0.00690***	0.00675***
			(4.43)	(5.35)	(7.00)	(5.97)	(5.91)	(6.84)
Years of Schooling				0.0649***	0.0671***	0.0587***	0.0543***	0.0516***
				(35.52)	(43.89)	(39.06)	(33.23)	(31.38)
Age				0.0180***	0.0169***	0.0181***	0.0179***	0.0175***
				(10.83)	(12.66)	(14.32)	(14.23)	(15.96)
Square of Age				-0.000218***	-0.000203***	-0.000203***	-0.000213***	-0.000218***
				(-13.31)	(-15.86)	(-16.71)	(-17.56)	(-19.99)
Marital Status=1					0.105***	0.104***	0.0945***	0.0870***
					(32.12)	(32.74)	(30.83)	(30.37)
Female=1					-0.203***	-0.205***	-0.227***	-0.237***
					(-24.64)	(-28.45)	(-41.78)	(-58.46)
English Ability=1						0.211***	0.193***	0.175***
						(56.66)	(47.35)	(44.49)
ACS Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	No	No	No	No	No	Yes	No
Country	No	No	No	No	No	No	No	Yes
Observations	1488693	1488693	1488693	1488693	1488693	1488693	1488693	1488693
R-squared	0.062	0.084	0.085	0.200	0.218	0.226	0.232	0.240

t statistics in parentheses
The dependent variable of this regression is logarithm of hourly earned income.
Model 1 includes year fixed effect along with the employment and family category fraction and use refugees as basis.
Model 2 adds landing cohort dummy which intervaled in 5 years period except 1972-1975 and year since migration variable to Model 1.
Model 3 includes family and employment fractions, year fixed effect, landing cohort dummy and it's interaction with year since migration.
Model 4 adds years of schooling, age and square of age to Model 3.
Model 5 adds English ability dummy to Model 4.
Model 6 adds marital status and female dummy to Model 5.
Model 7 adds region dummy which includes continental regions, Middle East and Mexico to Model 6.
Model 8 adds country of origin dummy to Model 6
* p<.10, ** p<.05, *** p<.01

Table 8: Outcome of regression in which the dependent variable is logarithm of hourly wage income.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Family Fraction	-0.283***	-0.328***	-0.328***	-0.154***	-0.115***	-0.110***	0.0240*	-0.0274
	(-9.27)	(-11.52)	(-11.55)	(-8.21)	(-7.86)	(-8.29)	(1.92)	(-1.06)
Employment Fraction	1.124***	1.384***	1.386***	0.814***	0.676***	0.617***	0.491***	0.222***
	(20.24)	(23.90)	(23.99)	(18.78)	(18.47)	(18.32)	(16.21)	(6.86)
Landing Cohort=7680		0.131***	0.0491	0.0108	-0.00724	-0.00408	0.00636	-0.0287
		(3.03)	(0.64)	(0.18)	(-0.17)	(-0.10)	(0.16)	(-0.92)
Landing Cohort=8185		0.201***	0.209**	0.0874	0.0544	0.0597	0.0483	-0.000612
		(2.89)	(2.35)	(1.32)	(1.13)	(1.32)	(1.17)	(-0.02)
Landing Cohort=8690		0.280***	0.225**	0.0762	0.0531	0.0622	0.0402	-0.0183
		(2.79)	(2.16)	(1.01)	(0.99)	(1.24)	(0.90)	(-0.54)
Landing Cohort=9195		0.250*	0.110	-0.00884	-0.0158	0.000273	-0.00562	-0.0540
		(1.85)	(0.80)	(-0.09)	(-0.24)	(0.00)	(-0.11)	(-1.41)
Landing Cohort=9600		0.313*	0.139	-0.0189	-0.0297	-0.0152	-0.0325	-0.0814*
		(1.89)	(0.83)	(-0.17)	(-0.38)	(-0.21)	(-0.56)	(-1.87)
Year Since Migration		0.0268***	0.0242***	0.0157***	0.0150***	0.0128***	0.0110***	0.00936***
		(3.99)	(3.66)	(3.55)	(4.93)	(4.71)	(5.12)	(5.97)
Landing Cohort=768~e			0.00223	0.00229	0.00239**	0.00210**	0.00151	0.00174**
			(1.19)	(1.47)	(2.20)	(1.99)	(1.56)	(2.15)
Landing Cohort=818~e			-0.00120	0.000769	0.00131	0.000838	0.000703	0.00118
			(-0.63)	(0.52)	(1.28)	(0.85)	(0.74)	(1.43)
Landing Cohort=869~e			0.000809	0.00238	0.00249**	0.00173	0.00161*	0.00199***
			(0.38)	(1.63)	(2.15)	(1.63)	(1.77)	(2.71)
Landing Cohort=919~e			0.00536***	0.00557***	0.00582***	0.00468***	0.00396***	0.00396***
			(2.86)	(3.71)	(5.09)	(4.25)	(4.00)	(4.90)
Landing Cohort=960~e			0.00896***	0.00883***	0.00922***	0.00780***	0.00741***	0.00718***
			(4.75)	(5.72)	(7.36)	(6.39)	(6.50)	(7.47)
Years of Schooling				0.0650***	0.0673***	0.0589***	0.0545***	0.0518***
				(36.10)	(44.70)	(39.69)	(33.60)	(31.71)
Age				0.0204***	0.0192***	0.0204***	0.0202***	0.0199***
				(12.48)	(14.53)	(16.24)	(16.22)	(18.24)
Square of Age				-0.000239***	-0.000224***	-0.000225***	-0.000234***	-0.000239***
				(-14.85)	(-17.62)	(-18.55)	(-19.52)	(-22.10)
Marital Status=1					0.103***	0.102***	0.0930***	0.0856***
					(31.39)	(32.10)	(30.31)	(29.91)
Female=1					-0.200***	-0.202***	-0.226***	-0.235***
					(-24.12)	(-27.82)	(-41.66)	(-57.67)
English Ability=1						0.208***	0.190***	0.174***
						(55.35)	(45.96)	(43.30)
ACS Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	No	No	No	No	No	Yes	No
Country	No	No	No	No	No	No	No	Yes
Observations	1363215	1363215	1363215	1363215	1363215	1363215	1363215	1363215
R-squared	0.069	0.094	0.094	0.222	0.242	0.251	0.256	0.265

t statistics in parentheses
The dependent variable of this regression is logarithm of hourly wage income.
Model 1 includes year fixed effect along with the employment and family category fraction and use refugees as basis.
Model 2 adds landing cohort dummy which intervaled in 5 years period except 1972-1975 and year since migration variable to Model 1.
Model 3 includes family and employment fractions, year fixed effect, landing cohort dummy and it's interaction with year since migration.
Model 4 adds years of schooling, age and square of age to Model 3.
Model 5 adds English ability dummy to Model 4.
Model 6 adds marital status and female dummy to Model 5.
Model 7 adds region dummy which includes continental regions, Middle East and Mexico to Model 6.
Model 8 adds country of origin dummy to Model 6
* p<.10, ** p<.05, *** p<.01

Table 9: Outcome of regression in which the dependent variable is employment status.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Family Fraction	-0.0123***	-0.0134***	-0.0134***	-0.00577***	-0.00426***	-0.00386***	0.00289**	0.00277
	(-7.00)	(-7.28)	(-7.25)	(-3.70)	(-2.85)	(-2.58)	(2.10)	(1.00)
Employment Fraction	0.0512***	0.0569***	0.0571***	0.0317***	0.0262***	0.0213***	0.0140***	-0.00158
	(18.08)	(17.03)	(17.04)	(12.50)	(10.79)	(9.23)	(5.71)	(-0.37)
Landing Cohort=7680		0.00439	-0.00836	-0.0103	-0.0108	-0.0108	-0.0102	-0.0109
		(1.57)	(-0.96)	(-1.30)	(-1.39)	(-1.41)	(-1.38)	(-1.48)
Landing Cohort=8185		0.00902*	-0.00788	-0.0115	-0.0126*	-0.0125*	-0.0127*	-0.0137*
		(1.95)	(-0.90)	(-1.44)	(-1.66)	(-1.67)	(-1.76)	(-1.92)
Landing Cohort=8690		0.0127*	-0.00981	-0.0130	-0.0142*	-0.0139*	-0.0145*	-0.0157**
		(1.89)	(-1.03)	(-1.49)	(-1.73)	(-1.71)	(-1.86)	(-2.05)
Landing Cohort=9195		0.0113	-0.0115	-0.0127	-0.0132	-0.0122	-0.0121	-0.0120
		(1.23)	(-1.02)	(-1.22)	(-1.40)	(-1.32)	(-1.36)	(-1.38)
Landing Cohort=9600		0.0144	-0.00842	-0.0121	-0.0128	-0.0121	-0.0123	-0.0122
		(1.25)	(-0.64)	(-0.97)	(-1.17)	(-1.13)	(-1.20)	(-1.22)
Year Since Migration		0.000833*	0.000257	-0.0000225	-0.0000422	-0.000251	-0.000337	-0.000439
		(1.81)	(0.54)	(-0.05)	(-0.11)	(-0.66)	(-0.92)	(-1.22)
Landing Cohort=768~e			0.000356	0.000374*	0.000371*	0.000354	0.000327	0.000318
			(1.51)	(1.69)	(1.67)	(1.60)	(1.49)	(1.45)
Landing Cohort=818~e			0.000488**	0.000530**	0.000545***	0.000511**	0.000493**	0.000488**
			(2.16)	(2.54)	(2.58)	(2.45)	(2.39)	(2.37)
Landing Cohort=869~e			0.000761***	0.000715***	0.000727***	0.000670***	0.000651***	0.000648***
			(3.22)	(3.22)	(3.26)	(3.04)	(2.96)	(2.96)
Landing Cohort=919~e			0.000832***	0.000680***	0.000685***	0.000592***	0.000551***	0.000534***
			(3.82)	(3.28)	(3.27)	(2.84)	(2.65)	(2.58)
Landing Cohort=960~e			0.000864***	0.000719***	0.000739***	0.000627***	0.000594**	0.000585**
			(3.54)	(2.92)	(3.09)	(2.62)	(2.48)	(2.47)
Years of Schooling				0.00286***	0.00290***	0.00220***	0.00199***	0.00206***
				(24.87)	(27.54)	(27.77)	(31.40)	(31.51)
Age				0.00223***	0.00171***	0.00179***	0.00183***	0.00190***
				(9.44)	(7.30)	(7.51)	(7.86)	(8.16)
Square of Age				-0.0000260***	-0.0000208***	-0.0000206***	-0.0000214***	-0.0000219***
				(-10.98)	(-8.86)	(-8.70)	(-9.08)	(-9.30)
Marital Status=1					0.0139***	0.0138***	0.0129***	0.0129***
					(20.61)	(20.57)	(19.75)	(19.83)
Female=1					-0.00592***	-0.00603***	-0.00736***	-0.00816***
					(-5.14)	(-5.41)	(-6.69)	(-7.51)
English Ability=1						0.0175***	0.0173***	0.0178***
						(17.81)	(20.39)	(20.41)
ACS Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	No	No	No	No	No	Yes	No
Country	No	No	No	No	No	No	No	Yes
Observations	1910897	1910897	1910897	1910897	1910897	1910897	1910897	1910897
R-squared	0.005	0.006	0.006	0.009	0.010	0.011	0.011	0.012

t statistics in parentheses
The dependent variable of this regression is employment status which is a categorical variable.
Model 1 includes year fixed effect along with the employment and family category fraction and use refugees as basis.
Model 2 adds landing cohort dummy which intervaled in 5 years period except 1972-1975 and year since migration variable to Model 1.
Model 3 includes family and employment fractions, year fixed effect, landing cohort dummy and it's interaction with year since migration.
Model 4 adds years of schooling, age and square of age to Model 3.
Model 5 adds English ability dummy to Model 4.
Model 6 adds marital status and female dummy to Model 5.
Model 7 adds region dummy which includes continental regions, Middle East and Mexico to Model 6.
Model 8 adds country of origin dummy to Model 6
* p<.10, ** p<.05, *** p<.01

Table 10: Outcome of regression in which the dependent variable is labor force participation.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Family Fraction	-0.0193***	-0.0202***	-0.0200***	-0.0132***	-0.000745	-0.000191	0.00457	0.000331
	(-3.64)	(-3.53)	(-3.48)	(-2.64)	(-0.22)	(-0.06)	(1.41)	(0.06)
Employment Fraction	0.0873***	0.0966***	0.0976***	0.0589***	0.0172***	0.00976**	0.00670	0.00734
	(10.31)	(9.90)	(10.00)	(7.19)	(3.43)	(2.06)	(1.44)	(0.92)
Landing Cohort=7680		0.0110	-0.0641***	-0.0701***	-0.0749***	-0.0749***	-0.0758***	-0.0760***
		(1.26)	(-3.06)	(-3.47)	(-3.85)	(-3.87)	(-3.99)	(-4.00)
Landing Cohort=8185		0.0167	-0.101***	-0.0981***	-0.104***	-0.103***	-0.104***	-0.105***
		(1.13)	(-4.43)	(-4.42)	(-5.74)	(-5.77)	(-5.96)	(-5.96)
Landing Cohort=8690		0.0175	-0.129***	-0.105***	-0.108***	-0.107***	-0.109***	-0.110***
		(0.82)	(-5.04)	(-4.07)	(-6.06)	(-6.10)	(-6.30)	(-6.33)
Landing Cohort=9195		0.00785	-0.132***	-0.0965***	-0.0944***	-0.0929***	-0.0946***	-0.0953***
		(0.27)	(-4.16)	(-2.92)	(-4.80)	(-4.80)	(-4.95)	(-5.03)
Landing Cohort=9600		0.0102	-0.136***	-0.108***	-0.106***	-0.105***	-0.107***	-0.107***
		(0.28)	(-3.47)	(-2.62)	(-4.71)	(-4.74)	(-4.86)	(-4.93)
Year Since Migration		0.000290	-0.00342**	-0.00245	-0.00261***	-0.00291***	-0.00296***	-0.00290***
		(0.20)	(-2.28)	(-1.56)	(-3.36)	(-3.86)	(-3.93)	(-3.88)
Landing Cohort=768~e			0.00205***	0.00227***	0.00230***	0.00227***	0.00230***	0.00228***
			(3.29)	(3.69)	(3.77)	(3.74)	(3.80)	(3.77)
Landing Cohort=818~e			0.00352***	0.00341***	0.00346***	0.00341***	0.00343***	0.00341***
			(5.78)	(6.01)	(6.28)	(6.23)	(6.30)	(6.23)
Landing Cohort=869~e			0.00502***	0.00387***	0.00384***	0.00375***	0.00378***	0.00377***
			(8.18)	(6.71)	(7.34)	(7.21)	(7.27)	(7.24)
Landing Cohort=919~e			0.00499***	0.00307***	0.00310***	0.00297***	0.00299***	0.00299***
			(9.01)	(5.67)	(6.19)	(5.94)	(5.98)	(5.96)
Landing Cohort=960~e			0.00559***	0.00373***	0.00377***	0.00360***	0.00363***	0.00362***
			(8.86)	(5.56)	(6.75)	(6.44)	(6.47)	(6.45)
Years of Schooling				0.00476***	0.00565***	0.00465***	0.00453***	0.00455***
				(15.21)	(30.93)	(34.99)	(36.63)	(34.13)
Age				0.0242***	0.0256***	0.0258***	0.0256***	0.0256***
				(30.03)	(37.27)	(36.98)	(37.52)	(37.53)
Square of Age				-0.000287***	-0.000301***	-0.000300***	-0.000300***	-0.000300***
				(-36.64)	(-43.43)	(-43.19)	(-43.10)	(-43.38)
Marital Status=1					-0.0256***	-0.0256***	-0.0249***	-0.0248***
					(-14.00)	(-14.13)	(-14.23)	(-14.09)
Female=1					-0.0737***	-0.0737***	-0.0746***	-0.0745***
					(-35.78)	(-37.14)	(-35.43)	(-35.23)
English Ability=1						0.0249***	0.0235***	0.0210***
						(15.97)	(17.92)	(16.33)
ACS Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	No	No	No	No	No	Yes	No
Country	No	No	No	No	No	No	No	Yes
Observations	2177462	2177462	2177462	2177462	2177462	2177462	2177462	2177462
R-squared	0.022	0.022	0.023	0.038	0.050	0.051	0.051	0.052

t statistics in parentheses
The dependent variable of this regression is labor force participation which is a categorical variable.
Model 1 includes year fixed effect along with the employment and family category fraction and use refugees as basis.
Model 2 adds landing cohort dummy which intervaled in 5 years period except 1972-1975 and year since migration variable to Model 1.
Model 3 includes family and employment fractions, year fixed effect, landing cohort dummy and it's interaction with year since migration.
Model 4 adds years of schooling, age and square of age to Model 3.
Model 5 adds English ability dummy to Model 4.
Model 6 adds marital status and female dummy to Model 5.
Model 7 adds region dummy which includes continental regions, Middle East and Mexico to Model 6.
Model 8 adds country of origin dummy to Model 6
* p<.10, ** p<.05, *** p<.01

Table 11: Outcome of regression in which the dependent variable is poverty status.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Family Fraction	-0.0601***	-0.0698***	-0.0698***	-0.0362***	-0.0347***	-0.0334***	0.000207	0.00168
	(-9.78)	(-11.55)	(-11.53)	(-10.63)	(-10.55)	(-11.33)	(0.09)	(0.41)
Employment Fraction	0.143***	0.186***	0.186***	0.0841***	0.0767***	0.0587***	0.0221***	0.00179
	(15.81)	(17.59)	(17.59)	(12.32)	(11.69)	(10.62)	(4.98)	(0.26)
Landing Cohort=7680		0.0188**	-0.0143	-0.0150	-0.0157	-0.0157	-0.0171*	-0.0184*
		(2.12)	(-0.75)	(-1.25)	(-1.24)	(-1.29)	(-1.76)	(-1.93)
Landing Cohort=8185		0.0316*	-0.00566	-0.0118	-0.0153	-0.0145	-0.0198**	-0.0205**
		(1.94)	(-0.27)	(-0.90)	(-1.14)	(-1.19)	(-2.07)	(-2.20)
Landing Cohort=8690		0.0448*	0.00682	-0.00168	-0.00604	-0.00428	-0.0117	-0.0126
		(1.86)	(0.27)	(-0.11)	(-0.41)	(-0.32)	(-1.12)	(-1.24)
Landing Cohort=9195		0.0415	0.00928	0.00379	0.000611	0.00434	-0.000406	0.000446
		(1.25)	(0.28)	(0.20)	(0.03)	(0.26)	(-0.03)	(0.04)
Landing Cohort=9600		0.0588	0.0293	0.0142	0.00952	0.0120	0.00571	0.00619
		(1.44)	(0.71)	(0.61)	(0.40)	(0.59)	(0.38)	(0.43)
Year Since Migration		0.00556***	0.00455***	0.00290***	0.00287***	0.00214***	0.00180***	0.00175***
		(3.32)	(2.80)	(3.15)	(3.10)	(2.71)	(3.15)	(3.16)
Landing Cohort=768~e			0.00101**	0.000801**	0.000794**	0.000728*	0.000708*	0.000698*
			(2.05)	(2.15)	(2.02)	(1.89)	(1.91)	(1.89)
Landing Cohort=818~e			0.00119***	0.00101***	0.00107***	0.000946***	0.000941***	0.000935***
			(2.60)	(3.07)	(3.08)	(2.84)	(2.91)	(2.90)
Landing Cohort=869~e			0.00127***	0.000933***	0.00101***	0.000792**	0.000804***	0.000792**
			(2.96)	(3.03)	(3.09)	(2.57)	(2.60)	(2.57)
Landing Cohort=919~e			0.000951**	0.000487*	0.000506*	0.000168	0.000135	0.000119
			(2.54)	(1.74)	(1.73)	(0.61)	(0.49)	(0.43)
Landing Cohort=960~e			0.000727	0.000286	0.000375	-0.0000152	0.00000676	0.0000148
			(1.08)	(0.54)	(0.72)	(-0.03)	(0.02)	(0.03)
Years of Schooling				0.0108***	0.0106***	0.00817***	0.00691***	0.00698***
				(69.94)	(73.10)	(73.30)	(71.91)	(74.55)
Age				0.00436***	0.00136***	0.00160***	0.00123***	0.00132***
				(11.90)	(4.37)	(5.18)	(3.82)	(4.14)
Square of Age				-0.0000302***	-0.000000756	0.000000465	0.000000129	-0.00000146
				(-7.95)	(-0.24)	(0.15)	(0.04)	(-0.44)
Marital Status=1					0.0763***	0.0763***	0.0765***	0.0764***
					(17.85)	(17.71)	(17.52)	(17.40)
Female=1					0.00366	0.00352*	-0.00382***	-0.00561***
					(1.57)	(1.81)	(-2.61)	(-3.92)
English Ability=1						0.0604***	0.0543***	0.0519***
						(41.60)	(46.07)	(42.17)
ACS Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	No	No	No	No	No	Yes	No
Country	No	No	No	No	No	No	No	Yes
Observations	2177462	2177462	2177462	2177462	2177462	2177462	2177462	2177462
R-squared	0.012	0.019	0.019	0.046	0.058	0.064	0.067	0.069

t statistics in parentheses
The dependent variable of this regression is poverty status which is a categorical variable.
Poverty was created using detailed income and family structure information about each individual and calculating the family income as a percentage of the appropriate official poverty threshold. As a result, if the individual is on the appropriate threshold or below it, he is assigned to 0.
Model 1 includes year fixed effect along with the employment and family category fraction and use refugees as basis.
Model 2 adds landing cohort dummy which intervaled in 5 years period except 1972-1975 and year since migration variable to Model 1.
Model 3 includes family and employment fractions, year fixed effect, landing cohort dummy and it's interaction with year since migration.
Model 4 adds years of schooling, age and square of age to Model 3.
Model 5 adds English ability dummy to Model 4.
Model 6 adds marital status and female dummy to Model 5.
Model 7 adds region dummy which includes continental regions, Middle East and Mexico to Model 6.
Model 8 adds country of origin dummy to Model 6
* p<.10, ** p<.05, *** p<.01

Table 12: Outcome of regression in which the dependent variable is English ability.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Family Fraction	-0.0895***	-0.122***	-0.122***	-0.0218**	-0.0222**	0.0905***	0.000946
	(-4.35)	(-6.26)	(-6.27)	(-1.97)	(-2.05)	(9.14)	(0.06)
Employment Fraction	0.502***	0.649***	0.651***	0.297***	0.299***	0.176***	-0.00565
	(14.62)	(18.21)	(18.24)	(12.38)	(12.52)	(9.11)	(-0.24)
Landing Cohort=7680		0.0572**	0.0287	-0.000696	-0.000545	-0.0136	-0.0371**
		(1.97)	(0.76)	(-0.03)	(-0.03)	(-0.66)	(-2.14)
Landing Cohort=8185		0.0936*	0.0625	-0.0134	-0.0132	-0.0411	-0.0738***
		(1.86)	(1.18)	(-0.44)	(-0.44)	(-1.58)	(-3.41)
Landing Cohort=8690		0.135*	0.0724	-0.0293	-0.0292	-0.0675**	-0.107***
		(1.77)	(1.01)	(-0.74)	(-0.74)	(-2.05)	(-4.03)
Landing Cohort=9195		0.125	0.0250	-0.0617	-0.0617	-0.0927**	-0.132***
		(1.24)	(0.25)	(-1.11)	(-1.12)	(-2.23)	(-4.11)
Landing Cohort=9600		0.172	0.0702	-0.0417	-0.0418	-0.0814	-0.125***
		(1.38)	(0.56)	(-0.59)	(-0.59)	(-1.57)	(-3.17)
Year Since Migration		0.0179***	0.0161***	0.0121***	0.0121***	0.0102***	0.00830***
		(3.51)	(3.25)	(4.35)	(4.36)	(5.24)	(5.72)
Landing Cohort=768~e			0.000708	0.00108***	0.00108***	0.00109**	0.00130***
			(1.08)	(3.03)	(3.03)	(2.37)	(2.99)
Landing Cohort=818~e			0.000601	0.00213***	0.00213***	0.00233***	0.00255***
			(0.69)	(4.19)	(4.19)	(5.08)	(5.90)
Landing Cohort=869~e			0.00195**	0.00361***	0.00361***	0.00387***	0.00401***
			(2.07)	(5.96)	(5.97)	(7.18)	(7.79)
Landing Cohort=919~e			0.00459***	0.00559***	0.00559***	0.00568***	0.00571***
			(5.56)	(9.51)	(9.52)	(9.75)	(10.37)
Landing Cohort=960~e			0.00510***	0.00646***	0.00646***	0.00667***	0.00661***
			(3.65)	(6.49)	(6.49)	(7.72)	(8.46)
Years of Schooling				0.0402***	0.0402***	0.0345***	0.0320***
				(112.64)	(98.94)	(103.97)	(88.67)
Age				-0.00403***	-0.00406***	-0.00625***	-0.00628***
				(-4.51)	(-4.59)	(-8.12)	(-8.35)
Square of Age				-0.0000206**	-0.0000202**	-0.0000114	-0.0000171**
				(-2.29)	(-2.28)	(-1.45)	(-2.24)
Marital Status=1					0.000566	0.00738***	0.00853***
					(0.33)	(5.93)	(7.89)
Female=1					0.00225	-0.0183***	-0.0255***
					(0.28)	(-3.13)	(-6.06)
ACS Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	No	No	No	No	No	Yes	No
Country	No	No	No	No	No	No	Yes
Observations	2177462	2177462	2177462	2177462	2177462	2177462	2177462
R-squared	0.039	0.078	0.079	0.265	0.265	0.288	0.320

t statistics in parentheses
The dependent variable of this regression is English ability which is a categorical variable.
If the individual does not speak English or does not speak well, he is assigned to 0.
If he is native or speaks well or very well, he is assigned to 1.
Model 1 includes year fixed effect along with the employment and family category fraction and use refugees as basis.
Model 2 adds landing cohort dummy which intervaled in 5 years period except 1972-1975 and year since migration variable to Model 1.
Model 3 includes family and employment fractions, year fixed effect, landing cohort dummy and it's interaction with year since migration.
Model 4 adds years of schooling, age and square of age to Model 3.
Model 5 adds marital status and female dummy to Model 4.
Model 6 adds region dummy which includes continental regions, Middle East and Mexico to Model 5.
Model 7 adds country of origin dummy to Model 5.
* p<.10, ** p<.05, *** p<.01