Essays on the Role of Ethnicity in Labor Market Outcomes and Human Capital

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Abstract

The first chapter of this dissertation examines the existence and cause of occupational hierarchies among immigrant worker groups in the United States. It first documents the persistent ranking of immigrant labor groups as reflected by their position in occupational distribution. We do this by examining the United States Census data for the period 1940-2010 and constructing the empirical occupational distribution of immigrant labor for major metropolitan regions using the Duncan Socioeconomic Index values. Having established the persistence of rankings across regions and time we estimate a structural model which maps immigrant workers into the occupational distribution on the basis of employers' perception of their perceived productivity. The estimates from the model strongly suggest that while individual human capital characteristics are important determinants of location in the occupational distribution a key factor, and the cause of persistence, is the presence of immigrant networks in occupations.

In the second chapter we examine whether ethnicity plays a significant role in inter-generational transfer of human capital. Relying on heteroskedasticity to identify parameters in presence of endogeneity, we revisit the Borjas ethnic capital hypothesis. In line with the literature, we find evidence that the OLS estimates of the effect of parental human capital on the children's educational attainment is biased upwards. The same is true for the estimates of the effects of the ethnic capital on intergenerational transmission of education. We also find that while parental capital has a relatively constant effect over time, the effect of ethnic capital has declined over the years. Interestingly, we also find evidence that women benefit from the quality of their ethnic environment while men appear to be unaffected by it.

INDEX WORDS: Occupational hierarchies, Immigrants, Networks, Socioeconomic status, Inter-generational transmission, Education

Dedication

In Memory of My Mom

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Chapter 1

Persistent Occupational Hierarchies Among Immigrant Worker Groups in the United States Labor Market (Co-authored with Francis Vella)

1.1 Introduction

According to data from the 1940 US Census immigrants from Canada and Northern Europe were more frequently employed in "better" occupations than those from Asia, South America and Southern and Eastern Europe. For example, 30 percent of Canadian and 36 percent of English immigrants were employed in white collar occupations compared to 18 percent of Italian, 21 percent of Polish and 11 percent of Mexican immigrants. Moreover, while the data show that by 2011 the share of white collar employment had grown from 30 to about 60 percent they also show that the disparity in the groups' respective shares of this type of employment had also grown. That is, the share in white collar employment had grown to 70 percent of Canadian and 76 percent of English immigrants compared to 38 percent and 18 percent for Polish and Mexicans workers respectively. While these figures suggest that some immigrant groups have collectively maintained higher shares of higher ranked occupations than other immigrant groups it is also interesting to examine whether these time series patterns at the aggregate level appear for specific regions. The evidence suggest they do. For example, in 1940 in Chicago 19 percent of Italian workers enjoyed white collar jobs compared to 15 percent of Polish workers while in Buffalo immigrants from Italy were also doing better than Polish with 24 percent of Italians and 16 percent of Polish respectively employed in white collar occupations. In the same regions in 2011 Italians still enjoyed higher shares with 46 percent of workers in white collar jobs in Chicago and 30 percent in Buffalo. Only 30 percent of Polish workers in Chicago and 20 percent in Buffalo were employed in white collar jobs. Similarly, in 1940 New York, 34 percent of Canadian and 26 percent of German workers enjoyed white collar jobs. In 2011, workers from both countries almost doubled their respective white collar employment preserving the ranking with 64 percent of Canadian and 45 percent of German workers employed in white collar jobs.

As human capital differences may explain the above it is interesting to examine the occupational distribution of individuals who are less likely to be allocated into occupations on the basis of observed skill. To do so we examine the shares in white collar occupations between 1940 and 2011 for unskilled workers, defined as individuals with at most a high school degree. In 1940, 25 percent of Canadian, 30 percent of English, 23 percent of German, 16 percent of Italian and 19 percent of Polish unskilled workers had white collar jobs. In 2011, Canadian and English workers had the highest shares, 47 and 49 percent respectively compared to 32 percent of Italians, 19 percent of Polish, 30 percent of Filipinos and 23 percent of Vietnamese. While the initial disparity might be partially attributed to the differences in the literacy rates and educational attainment associated with the earlier immigration waves, it is not clear why this pattern is preserved in later years, especially among unskilled individuals.

Although the above discussion is based on a very simple characterization of the labor market the data do provide evidence of ranking by immigrant groups. They suggest that immigrants from certain countries do better, in terms of occupational distribution, than immigrants from others and the "ranking" appears to persist across time and region. This paper provides a more detailed investigation for hierarchical sorting behavior across immigrant groups. That is, in areas with the immigrant groups appearing do we observe one group consistently doing better than another? Moreover, if immigrant hierarchies do exist which groups which do best, or worst, when paired and can we uncover the factors which determine the observed patterns?

We highlight that our focus is location in the occupational distribution and not the actual occupational choice. While the two are clearly related our choice of location is motivated by an earlier literature that finds immigrants are employed in different occupations depending on the region in which they locate. We examine whether the ranking of immigrant labor is invariant to the occupational composition of the region. Location in the occupational distribution captures the regional differences in the occupational composition and accounts for the "quality" of the workers present in the region, which better captures the hierarchy phenomenon.

While uncovering the existence and the determinants of immigrant occupational hierarchies is interesting in itself, it is also important because of its implications for the welfare of new immigrants and their children (see Borjas (1992), Borjas (2006a)). Hierarchies may not only determine employment opportunities of new migrants but, through inter-generational transmission of socioeconomic status, also those of subsequent generations (see, for example, Borjas (2006a)). The existence of persistent occupational hierarchies may lead to stagnation in the socioeconomic standings of immigrant workers and their subsequent generations. Moreover, this type of phenomena might also explain other socioeconomic behavior related to immigrants such as residential location.

Previous economic investigations of the labor market activity of immigrants in the United States have primarily focused on the impact the immigrants have on the native born (see, for example, (Altonji and Card (2007), Borjas (1994a), Card (1997), Card (2005), Ottaviano and Peri (2012)). These studies typically investigate the impact of immigration on various aspects of the native borns' labor market activity as measured by wages (see, for example, Card (1997), Ottaviano and Peri (2008), Ottaviano and Peri (2012)), employment opportunities (see, for example, Altonji and Card (2007), Card (2005)) and internal migration (see, for example, Borjas (2006b)). Studies on the performance of immigrants typically examine how the immigrants perform relative to the native born. An early literature examined the rate of convergence of immigrant workers wages to native born wages and saw the rate as a measure of assimilation (see, for example,Borjas (1994b)). Several recent empirical papers have considered how Hispanic and Asian American workers compare to natives (see, for example, Tolnay (2001),Bohon (2005) or Model (2002)) A feature of this work is that immigrants have been largely viewed as a homogenous group and their impact has been seen as a collective pressure on the native born. However, an examination of the immigration population and its composition indicates that the immigrant population comprises heterogeneous workers that differ on a number of dimensions including from where they come, when they came (see Borjas (1985), Borjas (1994b)), their capacity to speak English and other features which reflect their productivity and their capacity to perform in the labor market. Examining how these various features influence their position in the occupational distribution of migrants seems a valuable investigation.

Some recent work has studied various aspects of occupational choice of immigrants. For example, Model (2002) compared six nonwhite immigrant groups in the US and the UK and found that labor market outcomes across migrants from the same origin differ across destinations. Bohon (2005) shows that occupational attainment of Latino immigrants in the US is shaped by both, the place of origin and the destination. Patel and Vella (2013) provide evidence that the occupational choices of recent immigrants differ by destination and is influenced by the occupational choices of the previous cohorts of immigrants located in that destination. More specifically, there appears to be evidence that immigrants from specific countries cluster in particular occupations in different regions and that the allocation to these sectors generally does not depend on observed or unobserved skills. Moreover, the actual choice of low skilled occupations varies by metropolitan area. The choice of occupations of the early cohorts of immigrants was determined by both immigrants and regional characteristics. Immigrants subsequently developed occupational networks (Waldinger (1996), Waldinger (1994)) which attracted newly arrived immigrants to locate in these occupations (Patel and Vella (2013), Beaman (2012), Laschever (2009)). These networks contributed to shaping the labor market outcomes of generations of immigrants, especially among low skilled workers. Munshi and Wilson (2011) showed that even small differences in initial ethnic competition can have a long lasting effect on career choices.

Patel and Vella find persistence in occupational location across time and assign it to the presence network effects. We investigate whether an implication of these network effects is the creation of occupational hierarchies among immigrant worker groups. Consider two countries, A and B. From Patel and Vella (2013) we know that if immigrants from these two countries locate in the same region, they are likely to find employment in different occupations. Moreover, if the same groups locate in another region, they are likely to locate in different occupations. We ask the following question: If immigrants from country A are generally doing better than immigrants from country B in one region what is the likelihood that they are doing better in another region? Moreover, if we consider 3 groups or more do we see hierarchical patterns?

The next section describes the data and presents some evidence on the allocation into occupation of immigrants in the United States as captured by the occupational prestige scores. Section 3 provides evidence regarding the existence of occupational hierarchies of immigrant groups in the United States labor market. Section 4 introduces a structural model of occupational hierarchies based on the sorting of workers into sectors on the basis of productivity and provides a description of the estimation procedure. This section also provide a discussion of the estimates of the model. Section 5 presents the results from estimating the model. Section 7 investigates some implications of the results. Section 8 provides some concluding comments.

1.2 Occupational Prestige Scores and Immigrant Workers

Our empirical investigation employs data from 1940-2000 US Census and the 2011 5-year sample from American Community Survey (ACS)(Steven Ruggles et al., 2010). For the years 1980, 1990 and 2000 we use the 5 percent samples. For the years 1940, 1950 and 1970 we use the 1 percent samples. The Census Bureau no longer employed the long form questionnaire after 2010 and it was replaced by the ACS. Each yearly sample is an 1 percent sample of the population. We do not include the 1960 data as it does not contain information on the individual's geographical location at the metropolitan area level. We also do not use data prior to 1940 as the required information regarding the individual's educational attainment was not available.

To explore the existence and determinants of immigrant occupational hierarchies across time and space for the United States we begin by identifying the immigrant groups which have had a substantial and consistent presence in the United States. There are fifteen such groups and these are individuals from Canada, Mexico, Cuba, England, Italy, Germany, Poland, Russia , China, Korea, Philippines, Vietnam and India, Africa and the Middle East.[1],[2] These countries represent 68 percent of total

[1]Russia includes all individuals who declare Russia or USSR as country of birth

[2]Even though we consider some regions of origins for simplicity we will sometimes refer to them as countries.

immigration into the US in the period we examine. To reduce issues related to potential selection bias associated with the process by which individuals find work we restrict our sample to males aged 16 to 70 years. The groups in our sample represent 8 percent of all males aged 16 to 70 years and 70 percent of all immigrants of this age.

As our analysis is upon the occupational location of immigrants we require a measure which allows the ranking of occupations. We use the Duncan occupational prestige score (SEI). This score is computed based on the 1950 classification of occupations and represents a weighted average of educational attainment and income level associated with each occupation. The score was based on the median education attainment and income for 1947 survey of men only. It takes values between 0 and 100 noting that the highest value in our data is 96. The SEI score provides a consistent measure of occupational prestige using the 1950 classification of occupations and allows inter-temporal comparisons. However while the SEI is useful for our purposes it has some shortcomings. As the index values do not change over time they are unable to capture any significant changes in the prestige of the occupations if they occurred. Such a change might, for instance, manifest itself in large increase in average wages. However, it appears that SEI score captures a lot of variation in average wages associated with occupations. The correlations between the SEI score and average wages in each year in the period we consider are between 0.7 and 0.79. Moreover, in our sample, there are no occupations characterized with a low prestige score and unusually high average income or high prestige score and a low average income. Another shortcoming of any index measure is that the distances between the values are not really informative. That is, the "size" of the gaps in the socioeconomic status is not accurately reflected in this measure. Nevertheless, despite its limitation, it has certain advantages especially important our focus. Occupational hierarchies are a long term phenomena and we prefer a measure that is not affected by short term fluctuations. The SEI score is robust to any shocks to local economies that temporarily affect a status of an occupation but do not reflect its long term place in occupational distribution. Similarly, since it is computed based on native workers wages, it does not reflect any sorting into occupations by immigrants and its impact on wages.

Using our sample we rank countries in each metropolitan area based on the average occupational prestige score of their immigrants in that area for a given year. To avoid issues associated with small sample sizes we exclude all areas for which less than 50 individuals are present from the same country in a given Census year. This reduces our number of observations by 38 percent. As we investigate the relative positions of countries we also exclude metropolitan areas that have less than two different groups in a given Census year. This reduces the sample by an additional 10 percent producing a final sample consists of 112 metropolitan areas.[3] Table B.1 and Table B.2 report the changes in the composition of our sample for "all" and "unskilled" individuals. As the ranking of unskilled individuals is of interest most of the tables and discussion are reproduced for that subsample.

Prior to 1970 the largest immigrant groups were from Canada, Germany, Poland, Italy and Russia. However, from 1980 immigration from Mexico began to exceed that of any other group. Their share reached 46 percent of the whole sample in 2000 and 73 percent of the sample of unskilled workers in 2011. European immigration significantly decreased recently while immigration from Asia and African has increased. Since 1980, in addition to Mexico, China and the Philippines are the two largest sending countries. Among unskilled workers, China and Vietnam are the two largest groups after

[3] In a section below we describe and estimate our empirical model we limit the sample to post 1970 as a key variable, namely information regarding the individual's English proficiency, is only available after that year in the Census data. We lose 27 metropolitan areas due to this restriction.

Mexico. Total immigration from the Middle East has remained at around 3 percent. However, its share among unskilled workers has increased from 1 to 3 percent over time. Table B.1 and table B.2 summarize the changes in the sample composition of all and unskilled workers. Figure B.1 reports the distribution of the different groups by metropolitan area. Very few metropolitan areas have received large number of immigrants from many different origins throughout the whole period. Boston, Chicago, Detroit, Los Angeles, New York, Philadelphia and San Francisco have at least 5 different groups in every time period between 1940 and 2010. Other metropolitan areas appear more recently in our sample as they experienced large inflows of immigrants from 1980 onwards. Many metropolitan areas have only three large groups.

Table D.2 presents summary statistics for some variables of interest by country of origin by year. Consider both the changes across countries and the changes across time within countries. The average age varies from about 32 to 58 years. Between 1950-1970 immigrants from the early sending countries are generally older than in later years. There is also a minor increase in most recent years. The average age of those from the new immigrant countries has been consistently increasing and does not vary much between countries. While there are significant differences over time within countries, immigrants from Mexico, India, Korea, Vietnam, Africa and the Middle East are on average younger than the rest of the sample.

Large differences, both across time and countries, exist with respect to educational attainment as measured by years of schooling. Even though the trends are similar for all countries, with more individuals obtaining more than a high school degree, the distribution of educational attainment differs significantly across countries. Immigrants from Africa, Korea, Vietnam and India are the exceptions with relatively constant average years of schooling. The average individuals from each of these four countries are relatively skilled, with more than high school education. Indian workers completed on average 15 years of schooling, African and Korean 14 years, Vietnamese 12.5 years of schooling. The lowest levels of education are reported among Mexicans, with an average of less than high school degree throughout the whole period. Even though most of the countries experienced an increase in educational attainment, Italian, Polish and Cuban immigrants have relatively low educational attainment with averages of about 13 years of schooling. Those with the highest educational attainment are India, Canada, England, Germany, Russia, China, Korea, the Philippines and Africa. Each of these report averages above 14 years of schooling.

Analyzing the education trends in conjunction with the occupational prestige scores does not reveal an obvious positive relationship. In 1970, the average educational attainment among Canadians and Germans was about 11.4 years with a corresponding average occupational prestige score of 43 while the average worker from the Philippines completed over 12 years of schooling and was employed in a job with a prestige score of 37. In 2000 the average worker from England had 14.5 years of education and an occupation with a 56 prestige score while similar workers from Russia and the Philippines were employed in jobs with a prestige score lower by 9 and 14 points respectively. In the same year an average worker from Canada was employed in an occupation with a prestige score 4 points higher than a similar worker from Korea.

Rates of English proficiency also display significant variation across countries, and somewhat smaller within countries. Immigrants from Canada, Germany, England, the Philippines, Africa, India and the Middle East report proficiency, or close to proficiency, in English throughout the whole period. For most countries the share of individuals who speak English well remained relatively constant at about 70-85 percent between 1980-2011. Italian and Korean workers are exceptions as the fraction of workers proficient in English grew from 85 and 69 percent in 1980 to 95 and 76 percent in 2011, respectively. Mexico has the lowest shares of individuals who speak English. Only about half of the individuals report good knowledge of English. Also, workers from Cuba have relatively low share of English proficient workers over the entire period as only 68 percent of Cuban speak good English.

In determining each individual's position in the occupational distribution we can employ several approaches. One approach is to rank each occupation on the basis of the prestige score and rank workers according to the occupational prestige scores. One then describes a worker as being in the *pth* part of the occupational distribution if he is in the occupation which corresponds to that part of distribution. The problem with this approach is that it does not capture regional differences in the occupational distribution nor the "quality" of the other immigrants in the region. That is, the occupations in the *pth* part of the distribution in one region may not be the same as another depending on regional demand factors and which other groups are present. An alternative approach is to compute the empirical distribution of each region in each time period separately. An individual in the *pth* part of the occupational distribution now has a job in the *pth* part of the occupational distribution for that region in that time period. This is a more accurate characterization of the phenomenon that we are trying to describe. Most importantly, this measure of workers place in occupational distribution more effectively captures the hierarchy of workers.

Using this approach we consider the changes in the shares of workers employed in the "top" sector over time. For each metropolitan area in each time period we rank all workers based on the occupational prestige score associated with occupations in which they are employed in. The top 50 percent of individuals in each region are assigned to the top sector. Table B.4 summarizes the results for all and unskilled workers. While Indian, Canadian, English and Middle Eastern workers enjoy the highest shares of individuals employed in the top sector, Mexican and Vietnamese workers are least likely to be found in the top sector jobs. Filipino, Chinese, Italian and Korean workers experienced the largest increase in the shares in top sector of 19, 18, 17 and 15 percent respectively. Among unskilled workers, almost all groups enjoyed a steady increase with the exception of individuals from China and Africa who maintained their position in the occupational distribution over time. Contrasting these trends with a picture of the evolution of average SEI score presented in Table B.5 highlights the benefits of our approach in characterizing regional labor markets. Table B.5 shows that almost all groups enjoyed a steady increase in the average SEI score since 1940. [4] This suggests that all group's position on the labor market improved over time. However, as shown in Table B.4, the shares of individuals employed in the top sector grew at a smaller rate or did not change much at all. For instance, Italian workers average prestige score increased from 27 in 1940 to 49 in 2011, while the share of workers in the top sector changed from 49 to 66 percent. While the average SEI score almost doubled, the share in top sector increased by 33 percent. Between 1940 and 2011, Canadian workers enjoyed a 15 points increase in the average prestige score between 1940 and 2011, while their share in the top sector grew by as little as 4 percent. These discrepancies highlight that the rankings based on average SEI score do consider the regional occupational composition.

By using the changes in the differences between the average prestige scores of groups within a region we can examine the stability of the rankings. We first compute the difference in each metropolitan area for which the given pair is present and then average these differences over all regions in given year. Table B.6 and Table B.7 sum-

[4] India and Africa appear to show different patterns. However, there are only two metropolitan areas with large concentration of African and Indian workers in 1970, New York and Los Angeles and New York and Chicago respectively. Immigrants from both groups were frequently employed as Physicians and Managers and Administrators. In addition, Indians built large networks in engineering and African workers in actuarial occupations.

marize the results. In 67 percent of the whole sample and in 65 percent in the unskilled sample the ordering remained unchanged over the entire time period. This implies if in the first period in which we observe the two origins, immigrants from country A were, on average, doing better then immigrants from country B, they are generally still doing better in the last year we observe them. Moreover, in many instances, and particularly for unskilled workers, the average distance remains relatively constant. For example, in 1980 in an average metropolitan area where unskilled Canadian and Vietnamese workers were present, the latter were employed in occupations with an average prestige score lower by 7.2 points. In 2010, this distance was about 7.7 points. The distance between average prestige score between unskilled English and German or English and Italian workers varied slightly between 1.2 and 3.8 points, and 7.4 and 10.3 points, respectively, over the entire time period. However, some countries fell in the hierarchy, such as unskilled Russians against German, Canadian, English or Middle Eastern workers or unskilled Polish workers against Filipinos or unskilled Germans against Indians.

These patterns however do not convey information about the types of occupations different immigrant groups sort into. One explanation for the existence of occupational hierarchies is that, within regions, workers sort into different occupations. This could be driven either by regional labor markets characteristics or by group specific skills. In the first case, we should observe groups sorting into different occupation across regions, while in the latter, immigrants form particular group should always sort into the same occupations. Patel and Vella (2013) provide evidence that the choice of low skilled occupation varies by metropolitan areas suggesting that the allocation to occupation is not driven by specific skills which were brought by the immigrants. This further suggests that the hierarchies cannot be attributed to differences in group specific skills. However, even if workers sort into different occupations in different locations, within regions there could be significant overlap between popular occupations among groups in this region. In such instances the observed hierarchies would reflect differences in shares in each occupation within a region. To gain insight into the potential causes of the hierarchical pattern in the data we characterize each country's most popular occupational location in the US. An occupation is defined to be "popular" at least 5 percent of workers from country A are employed in this occupation. Using this measure of "popular", we now ask two empirical questions.

First, what is the frequency of a country developing large networks in the same occupations across different metropolitan areas? If at least half of occupations with networks of 5 percent or more are popular in two metropolitan areas we say that popular occupations are shared across these two regions. Table B.8 summarizes the frequencies of sharing popular occupations across metropolitan areas by skill level. The lowest incidence of shared popular occupations is reported among Polish immigrants in 1970. In only 15 percent of metropolitan areas in which they were present did they establish networks in the same occupations. For unskilled workers only in 18 percent of regions were the popular occupations were overlapping. On the contrary, Chinese workers in 1940 and Cuban workers in 1950 shared popular occupations in all regions. The same is true for unskilled Filipinos in 1950. However, these three countries were present in a small number of metropolitan areas at that time. As they subsequently spread across the country they located in different occupations across regions. For instance, in 1980 the incidence of sharing popular occupations across regions among Chinese workers fell to 50 percent and it continued to decrease reaching 38 percent in 2011. Among other countries, immigrants from Mexico and Africa show the least diversification across metropolitan areas while those from Canada, England, Germany, Poland and Russia tend to diversify the most. Immigrants from Asian countries locate in between with incidence of sharing popular occupation across metropolitan areas varying between 30 to almost 80 percent. Interestingly, for most countries, there seem to be more spatial diversification of popular occupations among unskilled individuals. Italy, China and India show an opposite pattern. Overall, the incidence of sharing popular occupations across regions is often below 50 percent suggesting that countries reveal a significant variation across popular occupations across metropolitan areas.

A second question is how often do different immigrant worker groups share popular occupations within the same metropolitan area? We find that about 60 percent of the popular occupations are unique to only one group in a given metropolitan area. This is quite remarkable given that popular occupations include very broad occupations such as managers or laborers, in which many immigrants find employment.

The answers to these two questions shed some light on the causes of the observed rankings. We observe significant polarization into occupations within regions and also confirm the lack of evidence for sorting based on group specific skills observed by Patel and Vella (2013). These data patterns suggest that the occupational hierarchies arise due to immigrant workers sorting into different occupations within regions and therefore suggest that occupational networks might play a significant role in maintaining the hierarchies over time. However, the evidence in this section might conceal the fact that the sorting of groups into occupations may very well depend on who else is in the region. This is explored in the following section.

1.3 Occupational Hierarchies Of Immigrant Workers

We begin our examination for occupational hierarchies with the simplest characterization of regional labor markets and make comparisons on the basis of the average SEI score for each of the immigrant groups in each region at each time period. Table B.9 presents the empirical frequency of each country (row country) being ranked above every other country (column country). The comparisons are made on the basis of year and metropolitan area calculations and the table summarizes the results of all possible pairwise comparisons. The top panel considers all individuals, the middle panel considers unskilled workers and the bottom panel considers the difference between the two. The lower panel summarizes how migrants with at most high school degree compare to all individuals.

First consider all individuals. There are many columns where the numbers are consistently high (or low) indicating that a specific group is consistently higher (lower) ranked than a number of the countries. Moreover, there are many entries throughout the panel which are either very close to 1 (or 0) indicating that every time immigrants from those particular two countries appear in the same area one of them is consistently achieving a superior (inferior) occupational distribution, as measured by the mean value of the SEI, to the other.

Consider some specific comparisons. Immigrants from India are almost always ranked first when they appear in a metropolitan area. Only in comparisons with Canada, England or China does the incidence of India being ranked first fall below 90 percent. In contrast Mexican workers are almost always found at the bottom of the occupational ladder. The only exceptions are when they are paired with workers from Vietnam or the Philippines. While India and Mexico represent the extremes there are many country comparisons in which a specific country dominates. For example, consider the following comparisons of countries with a long presence in the United States and with a substantial presence in many metropolitan areas. Germans are ranked above Italian and Polish workers in 92 and 87 percent of cases respectively. The almost exact same pattern is preserved among unskilled workers with 93 and 90 percent of cases in which German workers are ranked above Polish or Italian immigrants. However, when Germany is compared to Canada or England it is ranked first in only 18 and 15 percent of the cases respectively. Similarly, unskilled German workers are ranked above unskilled Canadian or English workers in only 18 and 19 percent of cases respectively. Italian and Polish workers are almost never ranked above English workers.

An additional pattern also emerges from the lower panel of this table. In many cases the ordering based on the whole sample and the sample of "unskilled workers only" is almost identical (entry near 0). For example, this occurs when Canada is compared with Poland, Germany, Italy, Vietnam, or the Philippines, when Poland is paired with Korea or Vietnam, when Italy is compared against Germany or the Middle East. However, for some countries, the pattern is almost reversed for unskilled workers. For example, consider comparisons involving China with Korea or the Middle East. For the whole sample Korea is ranked above China only 22 percent of times while for unskilled workers Korea is ranked first 87 percent of times. Workers from the Middle East rank above China in only 34 percent of cases in the whole sample but in 92 percent of the unskilled sample. Similarly, in the whole sample workers from Russia are doing better then workers from China in 74 percent of cases, while this fraction is only at 31 percent when only unskilled workers are concerned. In general, negative entry means that unskilled individuals from the row country are doing better then the group as a whole, while positive entry signifies the opposite .Another interesting pattern arising from the comparison of unskilled and all workers concerns India. While immigrants from India are unambiguously doing better than everybody else in the whole sample, in many cases unskilled Indian immigrants are not. This is especially true when paired with Korea, England, Germany or Canada. There also appears to be a lot of variation between the relative performance of Chinese immigrants and their unskilled counterparts.

As noted above the rankings in terms of average occupational prestige scores within regions are indicative of occupational hierarchies but they might hide important facts about occupational sorting of immigrant workers groups across regions. We have already established a significant variation in terms of popular occupations within groups across regions and within regions across groups. However, we have not yet excluded the possibility that immigrant workers sort into occupations based on what other groups are in the region. We now examine popular occupations for each pair of countries to shed some more light on what causes the persistence of occupational hierarchies. For simplicity, we will refer to the pair of countries as country A and B, where workers from country A are more often doing better than immigrants from country B. Since it is not feasible to present the results by pair of countries, we summarize the findings in a generic manner.

We define two countries as "sharing" popular occupations within a region if more than half of occupations that are popular among workers from country A are also popular among workers from country B. An occupation is considered popular among workers from country A if at least 5 percent of workers from country A are employed in this occupation. Therefore, the number of popular occupations differs by countries. For instance, in a region where there are 5 popular occupations among workers from country A, we say that A and B share popular occupations if at least 3 out of these 5 occupations are also popular among workers from country B. We find that in 21 percent of regions in which A and B appear together, A and B share popular occupations. In that case, the ranking between A and B reflects the differences in the shares in each occupation. Among unskilled workers this is less frequent as it occurs only in 12 percent of the regions in which A and B appear together. Therefore, in the majority of regions in which A and B appear together they established different popular occupations. In that case two scenarios are possible. First, both, workers from country A and workers from country B might be sorting into the same occupations across regions. [5] Immigrants from country A are ranked higher than immigrants from country B because, regardless of location, workers from country A are always doing better than workers from country B. This is the case in 22 percent of regions for all workers and in 57 percent of regions for unskilled workers. In the second scenario, workers from country A and B sort into different occupations within regions and they also sort into different occupations across regions in which A and B appear together. This occurs in 57 percent of regions where A and B appear together. Among unskilled workers this is a less common scenario and occurs in 31 percent of regions.

Thus the evidence indicates that there is substantial polarization into occupations within metropolitan areas within pairs of countries. This suggests that the stability of ranking could result from the fact that in metropolitan areas in which A and B appear together, typical occupations for A are more prestigious than popular occupations among workers from region B. We also find some evidence that among metropolitan areas in which given pair of countries appears, especially among unskilled workers, countries often establish networks in the same occupations across metropolitan areas implying that sorting into occupations across regions depends on the presence of other groups. These results highlight that occupational networks might contribute to the stability of the rankings over time and that labor market outcomes of immigrant workers depend on the presence of other groups.

In light of this last result, in addition to the shortcomings of comparisons based on average prestige scores, we now focus on comparisons based on location in the occupational distribution. Above we considered local labor markets split into two sectors. Even though the evidence based on such labor market characterization is suggestive

[5] We consider workers in one region to be doing the same as in other regions if at least half of the popular occupations in given region are popular in more than 50 percent of all regions in which A and B appear together in given year.

of the existence of occupational hierarchies we extend our analysis to three sectors. Therefore, for each region we return to the empirical distribution of occupations based on the SEI score and divide individuals into three distinct sectors of equal shares. We refer to these sectors as top, middle and bottom sectors.

As our definition of sectors is region specific the same occupation may fall into different sectors in different regions. For example, plumbers in Los Angeles and New York in 1990 were in the top sector while in 1950 New York and 1970 Chicago they are in the middle. Similarly, in 2000 Washington DC welders were located in the middle of the empirical distribution while in 2010 Newark they are in the bottom. To further highlight the differences between regions in terms of which occupations compose the different sectors Figure B.2 shows the distribution of the cut off points in the top and middle sectors across regions and time. It appears that the bottom sector composes of relatively similar occupations across the metropolitan areas over time. The spike in the distribution of the cut off points in the middle sector corresponds to occupations such as truck and tractors drivers, operative and kindred workers, carpenters and automobile-mechanics and repairmen. There is more variation in the distribution of the cut off points in the top sector reflecting more variation in the composition of the middle and top sectors across regions. The lowest cut off points correspond to clerical and kindred workers, cashiers and electricians in Salem, OR and Jacksonville, NC in 2011. Johnston, PA in 2000 and State College, PA in 2011 enjoy the highest thresholds and they correspond to professional and technical workers and managers, officials and proprietors. These differences in occupational composition of sectors highlight the differences in occupational distributions across regions.

A first step in examining the occupational hierarchies involves a characterization of each groups' allocation into the sectors over time. Table B.10 presents the shares of all and unskilled immigrant workers in the top, middle and bottom sector averaged over metropolitan areas.[6] First consider all workers. By 2011, Canadian, English, Chinese, Indian and Middle Eastern workers have on average over 80 percent of individuals employed in the top sector. Workers from Poland, Vietnam and Mexico have the smallest shares employed in the most highly ranked occupations. In 2011 only 9 percent of Mexican and 29 percent of Polish and Vietnamese workers had top sector jobs. At the same time 46 to 50 percent of Polish and Vietnamese workers find employment in the middle sector jobs. The bottom sector is dominated by Mexican immigrants with an average network size of 59 percent in 2011. A very small percentage of Canadian, English, German, Chinese, Korean, Indian and Middle Eastern workers are employed in jobs in the left tail of the empirical distribution.

The table for unskilled workers presents a similar picture. By 2011 all unskilled Canadians, English and German immigrants were employed in occupations located in the right tail of the empirical distribution of occupations of unskilled individuals. However, Chinese unskilled workers are significantly less likely to be employed in the top sector occupations than when all workers are considered and more likely to locate in middle sector jobs (45 versus 84 percent). This reflects that Chinese immigrants comprise either very skilled individuals or workers with very little formal skills. On the other hand, groups that have the smallest share of workers employed in top sector jobs, have higher shares of their unskilled workers employed in the top part of the empirical distribution. 29 percent of unskilled Mexican, 51 percent of unskilled Polish and 45 percent of unskilled Vietnamese workers are employed in top sector occupations. However, it is still the case that, even among unskilled workers, Mexican immigrants have the smallest shares of workers employed in the top sector and the highest shares of workers employed in the bottom sector. The observed inflation in

[6]The sectors are defined for the population of interest, so all or unskilled individuals, meaning that the sectors are not the same between the two tables.

shares among these groups can simply reflect the fact that these groups constitute the majority of the unskilled work force. Nevertheless, the observed patterns confirm that even though the sector allocation seem to be more equalized among groups when we limit the sample to unskilled workers and a clear hierarchical pattern still arises among groups.

We now focus on selected regions in which specific groups have a long history. For the sake of brevity we restrict Table B.11 to shares in top sector for selected regions. The occupational composition of the top sectors vary significantly across regions so we briefly discuss the popular top sector occupations of selected groups in selected regions. First consider countries that have a long history of immigration into the US. It appears that if a group did not do well in the region from the time it initially located in a region future migration into this region was suppressed. This results in the specific country/region observation dropping out of the sample. This occurred for Canadian workers in Providence and Springfield, English workers in Philadelphia, Germans in Buffalo, Cleveland and Pittsburgh, Italians in Buffalo and Hartford and Poles in Boston, Buffalo, Hartford, Pittsburgh and Springfield. In all these regions, the majority of migrants from aforementioned groups were employed in low prestigious occupations such as laborers and operative and kindred workers. In contrast, if a group managed to establish a network in the top sector early on, the position of the group in the empirical distribution improved over time. For instance the share of Canadian workers in Boston was 25 percent in 1940 and increased to 100 percent in 2011. Managers, officials and proprietors were among the most popular occupations among Canadian workers in 1940 and are still popular in 2011. Similarly German workers in Chicago and New York kept improving their position in the empirical distribution of occupations. Their share of top sector employment grew from about 29 to 100 percent between 1940 to 2011 in jobs such as managers, salesmen and mechanics and repairmen. In New York, the share of Italian and Polish workers also grew steadily from 23 and 16 percent to 49 and 42 percent, respectively. Both immigrant groups developed networks in clerical and sales occupations as well as insurance and real estate agents.

Countries with a more recent history of immigration can be broadly categorized into groups. The first group composes of Mexico, Cuba, China and the Philippines and these experienced a steady increase in the top sector jobs in regions in which they have a long history. For example, in 1950 Mexican workers were most successful in Los Angeles with 16 percent of workers employed in top sector jobs such as foreman, managers, salesmen and sales clerks. By 2011 this increased to 29 percent and Mexicans maintained large networks in theses occupations. Similarly, in regions where Chinese immigrants have long history, such as in New York or San Francisco, by 2011 their shares in top occupations such as jewelers, salesmen and cashiers exceeded 30 percent. Filipino workers steadily improved their position by establishing networks in professional occupations such as medical and dental technicians, technicians and professional and kindred workers in Los Angeles or sales and clerical and managerial occupations in San Diego and New York.

The second group consists of India, Middle East, Korea and Vietnam. Workers from these countries appear to maintain large networks in occupations in which they first locate and at the same time maintain their position in the local labor market. About 60 percent of early Korean immigrants in Los Angeles and New York were employed in occupations relatively high in the empirical distribution of occupations such as managers, clerks, cashiers, mechanics, welder, filers and grinders. Over time, they maintained large networks in these occupations and about 65 percent of Korean workers enjoyed top sectors jobs.

These crude patterns suggest that some countries are more likely to maintain large networks in the occupations in the same part of occupational distributions over time than others. However, it appears this is usually the case for more recent immigrants into the US. Most of the countries that show large improvements in the share in the top sector do so between 1940 and 1980. For the majority of the countries the changes in shares in the top sector in recent years are relatively small. This is also suggestive of the existence and persistence of occupational hierarchies. However, to establish the existence of such hierarchies in a systematic manner we turn to pairwise comparisons of countries within sectors on the basis of shares of workers employed in each part of the occupational distribution. Table B.12 and Table B.13 summarize the results for all and unskilled workers respectively [7]. India has the largest networks in the top sector occupations across the regions. Only Russian workers appear to have larger networks in these occupations in more than 50 percent of cases. Immigrants from Mexico are least represented in the top sector jobs. Vietnamese, Polish and Italian workers also have low shares in most prestigious occupations relative to other groups. In the middle sector occupations Mexican workers have relatively large networks in many metropolitan areas. Vietnamese workers have often the largest shares of workers in the middle sector.

For unskilled workers there is more persistence in the ranking of groups across metropolitan areas. This is reflected by 20 percent of zeros in Table B.13 in both sectors indicating that one group is always better the other when the two groups appear in the same metropolitan area. With the exception of England there are no absolute winners or losers. However, for some countries, when each pair of countries is considered separately, there appear to be significant polarization in both sectors.

[7] This table differs from Table B.9 since it compares the shares of workers in sectors and not the average prestige scores in metropolitan areas.

This suggests that unskilled workers from some origins are more likely to build large networks in more prestigious occupations out of the occupations in which unskilled individuals in our sample find employment.

The last two tables deliver conclusive evidence for the existence of hierarchical patterns. However, before we turn to a more rigorous analysis, let us focus on some possible causes of the patterns we have uncovered along observable differences between individuals employed in each sector. First consider the individual and group characteristics of workers in each sector. Table B.15 and Table B.17 show the summary statistics for all and unskilled individuals, respectively, that find employment in given sector. In each table the top panel compares individual in the top sector to all other individuals while the bottom panel contrasts individuals in the middle sector to those in the bottom sector.

Individuals in the top sector appear different to all other workers as reflected by age, education, English proficiency and fraction of established workers in the top sector in the whole sample as well as that comprising only unskilled individuals. Workers in the top sector are on average 2.5 years older, completed 3 more years of education, speak better English and have larger networks in the top sector by about 12 percent. Among unskilled individuals the differences are less pronounced. Unskilled workers in the top sector are on average 1.5 years older, completed extra half a year of schooling, speak better English and have larger networks in the top sector by about 6 percent. When workers employed in middle sector jobs are compared to individuals in the bottom sector they appear to differ only along education, English proficiency and network in the top sector dimensions. Arrival year as well as tenure of the immigrant group in the region, on average, does not seem to matter for the placement in the empirical distribution for unskilled workers but in the whole sample immigrants from origins that arrived earlier or with shorter tenure within region appear to do better in the labor market. When we restrict the sample to more recent time periods the importance of education and English proficiency and network size in the top sector increases for finding employment in the top and middle sector.

These national numbers might hide important differences across immigrant worker groups. Accordingly we analyze individual and group level characteristics by groups in Table B.14 and Table B.16. These tables show significant variation across groups along most of the dimensions, not only in the magnitude but also in the direction of the effect, especially among unskilled workers. Moreover, it also shows that origin introduces a significant heterogeneity in the characteristics of the average individuals employed in top, middle and bottom sector jobs.

First, for both the whole sample and the subsample of unskilled workers, education English proficiency and fraction of established migrants in the top sector are positively correlated with employment in the top and middle sector. Size of the network in the middle sector is negatively correlated with employment in the top sector and positively in the middle sector. However, there is significant variation within groups along most of the dimensions.

Comparisons across and within groups along educational attainment deliver some interesting evidence. First of all, individuals in the top sector completed more years of schooling for all groups. Among all workers Russian, Korean and Filipino workers appear most similar along this dimension with less than 2 years differences between individuals employed in top sector jobs and everybody else. Among unskilled workers Korean and African immigrants differ the least with less than quarter of a year difference. The largest difference of almost 4 years among all workers is found among Chinese immigrants. Even though workers in the middle and bottom sectors are more alike in terms of education, Chinese immigrants in the bottom sector are significantly less skilled than their counterparts in the middle sector with about 2.5 less years of schooling. This is no longer the case when we constrain the sample to unskilled individuals only which suggests that skills play a large role in placement in the empirical distribution of occupations.

Note that for all sectors it is often the case that the average years of schooling for some groups is significantly higher than among individuals from other group. For example, in the top sector, an average English worker completed just above 10 years of education, while an average Korean worker has almost a year and half more years of schooling. Similarly, in the middle sector, average Filipino worker completed about 11 years of schooling while an average Canadian worker only has only 9 years of education. Moreover, it is not uncommon that immigrants from some origins in the top sector have the same or less years of schooling than workers from other groups in the middle sector. For instance, an average Italian and Polish worker in the top sector completed about 9 years of schooling. Workers from Cuba, Russia, China, the Philippines, Korea, Vietnam, India, Africa and the Middle East all have on average higher schooling in the middle sector.

Similar pattern arises from the analysis of English proficiency. While for all groups better knowledge of English increase the chances of finding employment in top sector job, there is little difference between workers in the middle and bottom sector. This is especially the case for unskilled workers. Similar to the impact of education, the ability to speak English seems to matter most for Chinese worker. There is also significant variation within sectors and across groups. For instance, while almost all Filipino and African workers speak fluent English in the top sector, only 67 percent of Russian employed in top sector jobs report good knowledge of English. The same pattern appears among unskilled workers.

Chinese workers also differ significantly from other groups in terms of the importance of the arrival year and tenure in a region. Later arrival and shorter tenure seem to significantly increase the chance of top sector employment. Among other groups the effects are mixed. While Italian workers benefit most from a long history in a region Indian workers do better in regions with shorter history. In general, the countries with long history of immigration into the US tend to benefit from longer tenure within regions and individuals from more recent sending countries appear to do better in regions where they are present for shorter periods in time.

The differences in the age distribution across groups within sectors reflects the age distribution in the whole sample. In the whole sample the effect of age on the place in the empirical distribution varies across groups. For instance, Mexican and African workers employed in top sector jobs are on average 2.5 years older than everybody else. Average Chinese and Vietnamese workers are around 1.4 years younger when employed in the top part of the empirical distribution. Among the unskilled workers, within groups comparisons between sectors reveal that for the majority of the groups younger individuals are more likely to have top or middle sector job than a bottom sector one. However, with the exception of workers from the Philippines, Russian and Korea, these differences appear to be negligible. Unskilled Filipino workers constitute an interesting case as average worker in the top sector is 3 years younger than other Filipino workers and average worker in the middle sector is 5 years younger than an average worker in the bottom sector. Canadian immigrants are an exception here with older workers doing better then their younger counterparts.

Finally consider the role of the distribution of the established immigrants in the empirical distribution of occupations with sectors. The share of immigrants in the top sector is positively correlated with employment in the top and middle sector for all groups. Canadian, Chinese and Indian workers benefit the most from large presence in the top sector while Mexican and Cuban immigrants are the least affected. Among unskilled workers the largest effect is for workers from Canada, England and

Germany with the average network size in the top sector about 15 percent higher for workers in the top sector than all others. Share of established migrants in the middle sector has a small but negative effect on employment in the top part of the distribution. It does however contribute to employment in the middle part of the distribution although this effect is rather small. Polish and Vietnamese workers benefit the most from the presence of large networks in this part of the empirical distribution in terms of probability of finding employment in the middle sector. Unskilled Chinese workers have an average network size in the middle sector 18 percent larger among individuals holding middle sector jobs than among individuals in the bottom sector. This unusually strong effect can be attributed to the Chinese unskilled workers having especially strong networks in occupations in the middle part of the occupational distributions.

1.4 Estimating Structural Model of Occupational Hierarchies

Structural Model

The evidence above suggests that an individual's location in the occupational distribution appears to be related to both their own and their group's, as defined by country of origin, characteristics. This suggests these characteristics are determining the potential employers' perception of the worker's productivity. We now outline a structural model which is the underlying mechanism generating occupational location and thus occupational hierarchies. We then estimate the parameters of this model using the data from the US Census. The role of the model is to enhance our understanding of the factors generating the observed immigrant hierarchies. Moreover, with the parameters of the model we can consider some counterfactual occupational distributions which would occur if some of the conditioning variables took different values.

As our goal is to understand the occupational hierarchy of newly arrived immigrants we restrict our study to a certain population. First, to reduce the impact of assimilation on the rankings we consider immigrants who have arrived in the US within 10 years of each census year. Moreover, as we are focusing on comparisons across immigrant groups we require regions where the same immigrant groups are observed with regularity. Accordingly, we restrict our analysis to metropolitan regions where there are at least 50 (individuals) established migrants from each of at least 2 countries. Finally, since one of the variables which we expect is likely to explain occupational location is the ability to speak English we limit the empirical investigation to the post 1980 period as the information regarding the individual's capacity to speak English is unavailable for earlier periods. These considerations combine to produce a sample of four time periods and 83 metropolitan areas. The total number of time-region data points is 210 reflecting about 20 percent of all metropolitan areas in the 1980-2011 time period. The number of individuals in our sample is 373093. Our sample comprises immigrants born in the fifteen large sending countries and represents about 70 percent of all immigrant population between 1980 and 2011. To account for the presence of all new immigrants in regions we group individuals born in all other regions into one group which we refer to as "others".[8]

Our aim is to produce a characterization of the sorting process of immigrants into occupations such that the ranking we observe above can be explained. The economic process we envisage is the following. In each region there is an exogenous number of jobs and an exogenous number of immigrants. Moreover, we assume that the types of jobs, as reflected by the occupation type, is exogenous. Given the existence of these jobs and immigrants the problem facing the employer is to allocate the best workers

[8]Inclusion of this group into the estimation makes counterfactuals plausible. Omitting this group form the model necessarily implies redistribution into a sub sample of available occupations within particular region and dismisses a large group of available workers.

into the highest ranked occupations. The employers evaluate the productivity of each worker in each job and rank the workers. They then allocate the workers into the various jobs. We refer to a collection of jobs as a "sector" although this is not really an appropriate characterization. In each region the occupations are all ranked according to the index and then we aggregate them into sectors. This means that an occupation which is in the top sector in one region may not be in the top sector in another. We explore the implications of this below.

The sorting occurs as follows. Assume we divide the region into 3 sectors, where 1 is the sector comprising the highest ranked occupations filled by immigrants in that sector, 2 is the middle sector and 3 is the bottom sector with shares s_1, s_2 and s_3 respectively. We also assume that there are j immigrant groups with n_j workers each. If there are $N = \Sigma_{j=1}^{J} n_j$ workers the employers rank the workers on the basis of their productivity in the first sector and assign the top $s_1 * N$ workers to that sector. The employers then rank the remaining workers on the basis of their productivity in the second rank sector and assign the next $s_s * N$ workers to that sector. The remaining workers are then allocated to the bottom sector. The objective of the empirical work is to estimate the weights the employers put on worker characteristics in determining this allocation.

We acknowledge that these various assumptions regarding exogeneity is questionable but explaining each in the context of this simple model is beyond the scope of this paper. However, the assumptions are not unrealistic. First consider the exogeneity assumption regarding the number of workers. As documented in Jasso and Rosenzweig (1986) and Jasso and Rosenzweig (1995) the primary justification for immigration is due to family reunification. [9] Thus, if we examine a sample of newly

[9]Jasso and Rosenzweig (1986) and Jasso and Rosenzweig (1995) document that immigrants who come for a family reunification reasons constitute the largest group out of all immigrants and even the change in policy in 1990, which put a lower weight on family

arrived migrants in a certain region it does not seem unreasonable to assume that they are for reasons unrelated to issues associated with the distribution of occupations or relative wages. We also assume that the number of jobs is exogenous is to the process we are considering. This also does not seem unrealistic since the jobs we considering are generally low skill. The exogeneity of the number of jobs also assumes that the presence of immigrants is not changing the wage distribution in a manner which is changing the distribution of jobs across sectors. This seems to be less of an issue since we are focusing on rank in the occupational distribution rather than the demand for certain occupations.

The objective of the workers is to find employment in the highest ranked occupation. We exclude the possibility of sorting on comparative advantage and each worker would prefer to locate in the highest ranked sector. This does not appear to be unreasonable as the majority of the workers are unskilled and the evidence in Patel and Vella (2013) suggests that immigrants generally do not have occupation specific skills resulting in them being allocated into specific occupations. Note that we only consider employed individuals and while there may be unemployment in the model we are imposing that each of these individuals is employed.

The data generating process has the following form. Let $o = 1, ..., O$ denote the number of occupational groups (sectors) in the economy. Without loss of generality let the sectors be ordered, with 1 corresponding to the sector containing the highest ranked occupations. Each individual i from country j is characterized by a set of latent variables y_{ijo} which we define as a productivity in $(O - 1)$ sectors. [10] Let:

reunification, did not change this fact. As authors report, between 1969 and 1986, the share of adults who were granted permanent residence and were spouses of US citizens increased form 17 to 40 percent. Similarly, in 1961, 60 percent of all non-refugee immigrants were either spouses, parents, children or siblings of US citizens.

[10] Productivity in the lowest ranked sector is irrelevant in the model.

$$y_{ijo} = \begin{cases} \exp(x_{ij}\gamma_{jo} + z_j\alpha_{jo} + u_{ijo}) & \text{if } j = 1, \ldots, J \text{ and } o = 1 \\ \exp(x_{ij}\gamma_{jo} + z_j\alpha_{jo} + \zeta_o u_{ijo} + v_{ijo}) & \text{if } j = 1, \ldots, J \text{ and } o = 2, \ldots, O-1 \\ \exp(x_{ij}\gamma_{jo} + u_{ijo}) & \text{if } j = 0 \text{ and } o = 1 \\ \exp(x_{ij}\gamma_{jo} + \zeta_o u_{ijo} + v_{ijo}) & \text{if } j = 0 \text{ and } o = 2, \ldots, O-1 \end{cases}$$

for $o =, ..., O-1$ where $\{u_{ijo}\}_{i=1}^{N}$ and $\{v_{ijo}\}_{i=1}^{N}$ are $i.i.d$ sequences of $N(0, \sigma_{jo}^2)$ random variables.[11] $j = 1, ..., J$ corresponds to the large fifteen groups considered while $j = 0$ denotes everybody else in given region.

While we do not observe the workers productivity in equation 1.1 we observe their location in the occupational distribution. Let s_o denote the minimum productivity such that an individual is employed in sector o. If we let m_{io} denote a set of binary variables indicating whether an individual i is employed in sector o then:

$$m_{io} = \begin{cases} 1 & \text{if} \quad y_{ijo} \geq s_o \quad \text{and} \quad m_{il} \neq 1 \quad \text{where} \quad l < o \\ 0 & \text{otherwise} \end{cases}$$

To rank occupations we continue to employ the Duncan Socioeconomic Index. Using this index we employ the empirical distribution of occupations within each region. We assign each occupation a score based on its place in the empirical distribution and divide individuals into the three sectors accordingly. Individuals employed in occupations above the 66^{th} percentile of the empirical distribution are assigned to the top sector and individuals in occupations between the 33^{th} and the 66^{th} percentile are allocated into the middle sector. The remaining workers are employed in the bottom sector.[12]

[11] The choice of the functional form was driven by the performance of the estimator. It has no implications for identification.

[12] Extending the model beyond three sectors is trivial from a theoretical point of view, however, it proved to be challenging from the estimation perspective. It would also require a larger data set in order to reliably compute the networks sizes in each sector.

Employers rank individuals on the basis of their latent productivity y_{ijo}. This depends on both, the deterministic component, $x_{ij}\gamma_j + z_{jo}\alpha_{jo}$, and the random components, u_{ijo} and v_{ijo}. The individual specific characteristics which we employ in the productivity index include age, years of education and English proficiency. We also include the group level characteristics in the vector z and this contains the $network$ $size$ in the top and middle sector, the $length\ of\ stay$ of the group in metropolitan area as well as the $arrival\ year$ and $(arrival\ year)^2$. The $length\ of\ stay$ is measured in decades since arrival is continuous and denotes the arrival decade with 1 corresponding to 1940. $Education$ is measured with years of schooling. $English\ proficiency$ is a dummy variable indicating whether an individual speaks English. $Network\ size$ is measured as a share of established migrants from country j in metropolitan area m in year t that are employed in sector o. [13] Denote these shares as f_{jmo}. [14]

Our choice of variables in the productivity index is guided by the likely determinants of a worker's productivity and the importance of occupational networks for employment opportunities. Each of the variables appeared to be shown to be relevant in the discussion. An individual's age, experience and human capital are important determinants of productivity. The worker's age is a proxy for work experience. *Years of education* and *English proficiency* are the two measures of skills available in the data. However, for the immigrant labor force the measures of skills are unclear. Employers may not have the relevant information about the quality of education in the countries of origins. Employers might rely on easily observable characteristics to statistically discriminate among workers (Altonji and Pierret (2001)). Information about the group, such as the presence and strength of occupational networks and the

[13] Established migrants are individuals who arrived within more than 10 years from the Census year.

[14] Since time does not play an explicit role in our modeling framework the year subscript is suppressed.

group's history in the region serve as additional source of information for potential employers. As highlighted above, the evidence suggests that the individuals in the three sectors differ along all these dimensions implying that all these characteristic matter for worker allocation.

The model's data generating process is fairly general and allows for the coefficients to differ by sector and by country of origin. This permits the determinants of productivity to be different across sectors and country of origin. We also allow for the error variance to differ across sectors noting that the correlation between the error terms in the two sectors accounts for the unobserved correlation between the unobserved productivity in the two sectors.

Note that the coefficients vary by place in the occupational distribution and not necessarily by the nature of the occupation. Within each region workers are ranked based on their productivity index and therefore their place in occupational distribution depends on the distribution of productivities in the region. Identical individuals can therefore assume different positions in occupational distribution across sectors depending on the "quality" of other workers in the region. This allocation mechanism reflects that the value that employers place on certain characteristics depends on the distribution of these characteristics in the local labor market. For instance, a college degree might be of much higher value in regions with smaller fraction of individuals with a college degree. The implication of this allocation mechanism is that the weight of each characteristic in the productivity index is determined by the distribution of the characteristics of all workers and not by the characteristics of the occupations.

We highlight that while the model has attractive features it also has some shortcomings. For example, in addition to the issues related to the exogeneity concerns discussed above the model does not incorporate equilibrium behavior by workers and employers. Ideally the model would allow the number of workers and jobs to vary depending on the quality of the workers, wages and local demand conditions. The model might also allow the employers and workers to move across regions. While we feel that these would be positive extensions to the model we also are of the view that even when failing to allow for this behavior the model provides an insightful description of the data.

Estimation Procedure

While the model in 1.1 and 1.4 is simple it would be difficult to directly estimate its parameters due to the productivities being latent, the multiple outcomes of the model and the sequential nature of the allocation process. Even if one were able to exploit the distributional assumptions to construct a likelihood function the multiple integrals involved would make estimation challenging due to the correlation of the error terms across sectors. Estimation would be particularly difficult if the number of sectors grew to a large number. That is, in the presence of larger data sets we could allow the number of sectors to be very large. However, irrespective of the number of sectors it is straightforward to simulate the data from our model given our assumptions regarding the various exogenous features of the model. Thus to estimate the model we use the indirect inference procedure. (Gourieroux et al., 1993) We estimate an auxiliary model characterized by a set of parameters to explain the immigrant shares of occupations we observe in the data. We then use our model to simulate data for given values of the "structural" parameters and we choose the structural parameters such that the parameters for the auxiliary model on the simulated outcomes are "close" to the parameters for the auxiliary model for the true data.

Let β denote the structural parameters of the model and k_1 and k_2 the number of individual and group variables in the productivity index, respectively. The β vector contains the parameters in the productivity index, $\{\gamma_{jo}\}_{j=0}^{J}$, $\{\alpha_{jo}\}_{j=1}^{J}$, $\{\sigma_{jo}^2\}_{j=0}^{J}$ and ζ_o

in each sector o. Let $\hat{\theta}$ denote the estimates of the auxiliary model on the real data and $\tilde{\theta}^m(\beta)$ denote the corresponding estimates on the simulated data where $m = 1, ..., M$ denotes the number of simulations. The data is simulated using observed data and an assumed value of β. For each of the simulated data sets we estimate the auxiliary model and obtain $\tilde{\theta}^m(\beta)$. Let $\tilde{\theta}(\beta) = \frac{1}{M}\sum_{m=1}^{M}\tilde{\theta}^m(\beta)$ so the average vector of the estimated parameters of the auxiliary model. We choose the values of β such that:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}}\,(\hat{\theta} - \tilde{\theta}^m(\beta))' W(\hat{\theta} - \tilde{\theta}^m(\beta))$$

where W is a positive definite weighting matrix. [15]

Care must be taken when estimating models with endogenous discrete variables using indirect inference. (Keane and Smith, 2003) Small changes in structural parameters lead to jumps in the simulated data which make the objective function change discretely .The objective function is not a smooth function of the structural parameters and it is not possible to use gradient based methods to estimate the model. Since our model has this issue we employ a solution proposed by Keane and Smith (2003).

An important feature of indirect inference is that the auxiliary model need not be "correctly specified" and the estimates of the auxiliary model's parameters do not need to have the usual desirable properties. Moreover, while the choice of the moments to match between actual and simulated data is theoretically unimportant, subject to issues related to identification, our view is that the auxiliary model should be chosen such that it explains some important features of the data. In our case, the choice of the moments is directly motivated by the model. Since we are interested in the shares of immigrant workers in sectors in regions we will focus on the parameters in a reduced form explanation of those shares. According we use an auxiliary model that predicts

[15] We use an identity matrix since our auxiliary model includes additional moments, we cannot apply the optimal weighting matrix as described in (Gourieroux et al., 1993)

the shares and match the parameters of this model. We estimate the following linear regressions separately for individuals from large groups and the others:

$$m_{ijo} = \begin{cases} x_{ij}\xi_{jo} + z_j\mu_{jo} + f_{-jo}\omega_{jo} + \eta_{ijo} & \text{if} \quad j = 1, ..J \\ x_{ij}\xi_{jo} + f_{-j}\omega_{jo} + \eta_{ijo} & \text{if} \quad j = 0 \end{cases}$$

where f_{-j} denote J-1 shares of other groups in the top sector. The inclusion of the shares of other groups helps predict the shares more accurately. This yields $2(J+k_1+k_2+1)+J+k_1+1) = 84$ parameters. To aid identification of the variances and covariances between the errors we add the estimates of the covariance matrix of the residuals of the linear probability models and this yields four additional parameters.

As mentioned above, the presence of discrete random variables poses some additional challenges in the estimation strategy. In our model small changes in the structural parameters result in discrete changes in the indicator functions $m^m_{ijo}(\beta)$. To overcome this we use a generalization to the indirect inference procedure. (Keane and Smith, 2003) We substitute m^m_{ijo} with a continuous function of the latent productivity, $g(y^m_{ijo}(\beta); \lambda)$, such that:

$$g(y^m_{ijo}(\beta); \lambda) = \frac{\exp((y^m_{ijo}(\beta) - s_o)/\lambda)}{1 + \exp((y^m_{ijo}(\beta) - s_o)/\lambda)}$$

where λ is the smoothing parameter and s is the minimum productivity guaranteeing employment in the top sector.[16] The choice of the smoothing parameters is important as larger values of λ result in a smoother objective function but may cause a large bias. We use $\lambda = 0.05$ and $m = 10$ noting that increasing the number of simulations appears to have little effect on the estimates and increases the time burden significantly.

[16] We follow Smith and Keane (2003) in the choice of the g(.) function. As long as $g(y^m_{ijo}(\beta); \lambda)$ converges to $m^m_{ijo}(\beta)$ as λ goes to zero, any continuous function of the latent productivity would result in consistent estimates of the structural parameters. This function was also used in (Altonji et al., 2013).

Results

Within each sector we restrict the coefficients to be the same for the fifteen large groups but allow them to differ for the group of others. Therefore, in each sector o, $\gamma_j = \gamma_1$ and $\alpha_j = \alpha_1$ for$j = 1, ..., J$ and $\gamma_j = \gamma_0$ and $\alpha_j = \alpha_0$ for $j = 0$.[17] For identification we normalize the coefficient on education in the top sector to 1 for the "large" group and also for the "others" group. We also normalize two of the variances to 1. As we noted above our results are based on $\lambda = 0.05$ and 10 simulations. However, the Monte Carlo evidence based on our model suggested that the relatively small number of simulations did not appear to have a substantial effect on the bias.[18] All explanatory variables are scaled to ensure that the entries in the Hessian are of the same order of magnitude to aid performance of the search algorithms. The covariance matrix is estimated following (Gourieroux et al., 1993) as explained in details in Appendix A, however, since our auxiliary model consist of additional moments the estimated standard errors are underestimated[19].

Before proceeding a discussion of the main results first consider the estimates from the auxiliary model. It is our view that the indirect inference procedure is more attractive in instances where the auxiliary model is associated with the estimation of an object of substantial interest in the structural model. In our empirical investigation the objects of interest are the fractions of each of the immigrant groups' workers

[17]Allowing the parameters of the productivity index to vary by groups proved to be not feasible due to a large number of resulting structural parameters.

[18]Implementation of the estimation strategy described in previous section proved to be challenging. The objective function exhibits multiple local minima which makes the search for the global solution time intensive. We carefully examined the neighborhood of every parameter estimate to ensure that we have found a global minimum.

[19]Given the fact that the analytic standard errors rely on numerical derivatives and therefore allow us to manipulate its magnitude, the value added form the derivation of asymptotic covariance matrix in this setting seems low. Therefore we report the analytic standard errors noting that they are underestimated and also their magnitude vary with the choice of the delta in numerical derivatives.

located in the various "sectors". To examine our auxiliary model's capacity to reproduce those shares in Figure B.3 we report the relationship between the predicted and actual values for our auxiliary model for the actual data in the top and middle sector. The model performs very well. This is not surprising as the conditioning set of variables in each of these equations is rich. Most notably it includes the shares of each of the other immigrant groups and these appear to be important explanators. The other variables included in the auxiliary model, recalling that the moments we are matching are the model's coefficients and not the predictions, are all the variables included in the productivity index. The auxiliary regressions also include individual's age, educational attainment, English proficiency as well as characteristics of the group defined as country of origin of an individual, such as size of the network in top and middle sector, the year a group is first present in the region in large numbers (*arrival year* and $arrivalyear^2$) and the tenure of the group in the region (*length of stay*). In addition to the other groups' shares almost all other regressors in both top and medium sector for large groups and the group of others had a significant role in predicting the shares. Only age does not play an important role in explaining the placement in the middle sector when immigrants from origins other than the 15 large sending countries are considered.

Table B.19 presents the estimates for the structural model. For each sector the coefficients are restricted to be the same for the "Larger groups" noting that for the "Others" category we do not include the variables describing the characteristics of the country of origin and therefore size of the network in the top and middle sector, *arrival year*, $arrivalyear^2$ and *length of stay* are excluded from the productivity index for the "Others" category. Given that these individuals are of very different origins construction of these variables seem implausible. Given the motivation for the inclusion of these variables in the productivity index it seems unreasonable to assume that such a diverse group can provide valuable information to the employer. Due to the normalizations employed throughout the model it is not straightforward to directly interpret the coefficients. To examine the impact of a change in the value of the explanatory variables it is necessary to simulate the model and we do so below. However, from visual inspection of Table B.19 we can directly interpret the sign of the change from an examination of the sign of the coefficient. This allows us to draw conclusion regrading what individual's features positively affects employers evaluation of the worker's productivity. Focus on the "Larger" groups first. Assuming that years of schooling positively contribute to the employers' assessment of workers productivity all of the explanatory variables appear to have a positive effect on the evaluation of worker's productivity in the top sector. Employers seem to value older workers, those with a better knowledge of English, those coming from origins that have long history in the region and established networks in the occupations in the top part of the occupational distribution. The size of the network in the middle sector does not seem to play a role in the top sector jobs but has a large and positive effect on employers assessment of the productivity of workers in occupations located in the middle part of the occupational distribution. Moreover, the size of the network in the top sector appears more important for the assessment of productivity in the middle sector than the size of the network in the middle sector jobs. English proficiency plays a smaller role than in the top sector. However, in contrast to the top sector, in the middle sector, employers seem to prefer younger workers who arrived later and are of origins with shorter histories in the region, although, it does appear that the early cohorts of workers were highly valued in the earlier years in the sample. When evaluating productivity of workers with no "Large" group affiliation all the individual characteristic have positive weights in both sectors. While age of the workers and their ability to speak English well have similar relative magnitudes in both, top and middle sector, education appears to be of greater importance for employers in occupations in the middle part of the occupational distribution.

Contrasting the relative magnitudes of the estimated parameters for both groups, "Large" and "Others", within sectors delivers additional evidence. The weights for workers without a "Large" group affiliation are approximately half of the magnitude of the corresponding weights in the tops sector. In the middle sector, there seem to be a bigger variance in the weights of each characteristic for the assessment of workers productivity. Given the relatively large coefficients on the size of the network in the top and middle sector as well as on *arrival year* and $(arrival\ year)^2$, it appears that employers in occupations falling in to the middle part of the distribution, are more likely to statistically discriminate based on the information they have about the group's history in the region. The large weight on educational attainment as well as a hundred percent higher weight on English proficiency among workers without "Large group" affiliation indicate that such workers need to demonstrate significantly higher skills to compensate for the lack of the network.

Model Fit

To examine our model's within sample predictive performance we employed the actual data and the parameters estimates and conducted 100 simulations. For each simulation we calculate the shares of workers from each origin in each region in each sector.[20] We then computed the occupational distribution based on the averaged shares for each of the group and rank countries within each region based on the average fraction of workers employed in each sector. Table B.18 provides the fraction of rankings in

[20] For the lack of better notation, region here denotes metropolitan area-year combination.

the top, middle and bottom sectors for every pair of countries across regions that is predicted correctly.[21]

The model appears does well in the top sector predicting the correct ranking for 80 percent of the pairings. In general the ability to correctly predict the ranking depends on two factors. First, if the actual shares of workers employed in a given sector are relatively spread out in the region the model is effective. The second issue is related to the sample size. If we only observe a pair of countries in a small number of regions the average performance of the model is relatively low. For example, there are only 6 regions with large groups of new Cuban and Vietnamese workers and in 3 out of these regions, the shares of each group in the top sector are almost the same. Thus, the model predicts correctly only 33 percent of the rankings between Cubans and Vietnamese workers. Alternatively, when Indian workers are compared to Koreans, 74 percent of the rankings in 47 regions are predicted correctly. In the middle and bottom sector, the predictions are, on average, less accurate as in the top sector. The model correctly predicts 70 and 74 percent of the rankings in the middle and top sector, respectively. This decline in the model fit could be attributed to a decline in sample size over which the parameters of the productivity index are estimated. The loss in average performance is driven by the decline in the accuracy of predicting the shares in regions with relatively small number of new migrants from given group. However, while the model's capacity to predict is variable the correct percentages presented in the table suggests it performs well.

[21]When computing predicted shares we limit the sample to metropolitan areas with at least 30 new migrants in each group to avoid taking averages over small cells.

1.5 Implications of Results

The model's capacity to explain the observed ranking suggests the model is performing well. However, this does not provide insight into establishing which of the explanatory variables are the driving forces in generating the rankings. To assess the quantitative effect of each of the explanatory variables in the structural model we perturb each of the variables in isolation for each group and evaluate the impact on the resulting rankings. This provides some indication of the changes in the explanatory variables required to alter the ordering between groups and therefore inform us about the role each characteristic play in generating the rankings. As we are taking averages over individuals within regions we limit the sample to only regions with large groups of new migrants.

We first simulate the data using observed data and the structural model parameters estimates to obtain the distribution into sectors of all groups. For given values of the group and individuals characteristics of interest we change the value of a specific characteristic for all individuals of considered origin and perform the simulations again to obtain a new allocation of workers into occupational distribution. For all experiments we simulate the data 100 times. The tables show the changes in rankings between every pair of countries. The rankings are based on average shares in each of the sectors and country A is considered ranked above country B in sector o if the share of workers from country A in sector o is higher than the share of the workers from country B.

Table B.20 and table B.21 present the results for the 10 percent increase in the share of established migrants in the top and middle sector respectively. Table B.22 corresponds to increasing schooling of individuals from given origin by one year. Table B.23 shows the effect of increasing English proficiency of all group members and table B.24 summarizes the changes due to ten years earlier arrival of the group and, simultaneously, a ten years longer tenure in a region. In each table we alter the given characteristic for one country at a time (row country) and follow the changes in pairwise rankings between the row country and every other country (column country) in all three sectors. If the altered regressor has unambiguously positive (negative) effect on productivity the change in ranking can only occur if, initially, in given region, the row country was ranked below (above) the column country. Therefore, each entry in table B.20 - table B.24 represents the fraction of such eligible regions in which the ordering between the two countries has changed in response to the change in the underlying characteristics of the row country. Since reasonable changes in individual's age did not result in meaningful changes in the hierarchies among groups we exclude it from the tables.

Before turning to the analysis of the role played by each characteristic note that in the top sector the direction of the change in the rankings is always consistent with the sign of the coefficient. Since for "Larger" groups all coefficients have positive signs the change in ordering in the top sector is always in favor of the group whose characteristic is affected by the experiment. In the middle and bottom sector, however, there are two channels through which the change in each characteristic affect the ranking of groups. The first is a direct effect through the productivity index while the second is an indirect effect through a composition of individuals who do not find employment in the top sector. Therefore, it is not straightforward to assess the direction of the overall change unless the sign of the coefficient in the top and middle sector is the same. This is the case for educational attainment, English proficiency and the allocation into occupational distribution of established migrants. A change in ordering between two countries in response to an increase in those variables indicates an improvement in the position in occupational distribution of the group affected by the change in the characteristic. This is not the case for individual's age and group arrival year and tenure in the region. The direction of the effect induced by changes in these three characteristics is ambiguous in the middle and bottom sectors.

Now turn to the assessment of each variable's role in generating the rankings. Consider individual characteristics first. Increasing schooling by one year affects, on average, 5, 4.5 and 6.5 percent of rankings in the top, middle and bottom sector respectively. At first sight, these effects might appear small. Recall however, that these numbers reflect the fraction of rankings that change as a result of the changing the underlying characteristic and not just increase in the shares in respective sectors. Therefore, the magnitudes of the effects confirm that these characteristics play an important role in generating the hierarchies. Polish, Italian and Cuban workers appear to benefit the most from higher educational attainment in the top sector as it would affect on average 10 to 15 percent of rankings with other countries. Similarly, increasing the ability to speak English of all individuals of certain origin affects, on average 5, 4.5 and 6.5 of all rankings in the top, middle and bottom sector, respectively. For Cuba, Vietnam, Poland and China, English proficiency seem to be very important. If all Cuban workers were able to speak fluent English then in 63 percent of regions in which Cuban workers are ranked below Italian immigrants the ranking would be reversed. Similarly, If all Korean workers would be proficient in English, in approximately quarter of all regions where Koreans are ranked below workers from the Middle East, Africa, India, China, Russia or Canada the rankings would be reversed. In the middle sector, the effects of educational attainment are of similar magnitudes across groups as in the top sector. However, English proficiency appear to play an even bigger role in determining the hierarchies than in the top sector. For instance, increasing knowledge of English would affect about 45 percent of rankings in the middle sector in regions in which Korea is paired with Italy and about 35 percent when it is compared to Canada or Poland. In the bottom sector, the role of English proficiency is significantly smaller across countries while the educational attainment continues to play an important role in determining the rankings between groups. These results suggests that the basic skills of workers play an important role in generating the rankings between groups in all sectors. Even though these results are not surprising the magnitude of these effects has non trivial policy implications as it appears that promoting mastering English skills among disadvantaged immigrant worker groups can generate a long term positive effect on their performance on labor market.

Next consider characteristics of the countries of origin. Earlier arrival and longer history in the region appear to have a similar effect on the rankings in the top sector. Only Italian workers do not appear to benefit from longer history in the region although they significantly benefit from a larger networks in the top sector. However, in the middle and bottom sector, arrival year and tenure in the region appear to have the smallest effect on rankings. On average, 3 percent of the orderings in the middle and 4 percent in the bottom sector change in response to a ten years earlier arrival and simultaneously ten years longer tenure in a region. The placement of established workers in the occupational distribution seem to play a more significant role in determining the hierarchies in the middle and bottom sector, especially among workers from Canada, the Middle East, India, Korea and China. On average, in 10 percent of regions in which workers from one of these countries are ranked below any other immigrant group, the ordering would change in favor of these countries due to a 10 percent increase in the size of the network of established migrants in the top sector. Considering that the change in the network size we impose can be rather small for groups with a small representation in the top part of the occupational distribution these effects appear to be very large. The network effects through the network in the middle sector are smaller but still affect up to 10 percent of orderings in the middle sector and up to 6 percent of orderings in the bottom sector. The effects in the top sector are negligible and therefore it is omitted from the table. Larger networks in occupations in the middle part of the distribution would benefit workers from Korea, Poland, Russia, Italy and Mexico the most as it would affect up to 27 percent of rankings with selected countries in the middle sector and up to 20 percent of rankings in the bottom sector thus significantly improve their position in occupational distribution.

The capacity to affect the hierarchies between groups varies by characteristics. There is significant variation in the magnitude of the effects of each of the characteristics across countries of origin. However, the results in this section clearly suggest that many of the analyzed characteristics play an important role in the process of generating the hierarchies. Educational attainment, English proficiency and distribution of established migrants in the occupational distributions appear to be the most important. However, given the large number of zeros in the tables it also appears that the orderings between some countries do not respond to reasonable changes in underlying characteristics. For example, it is very difficult to change the position of Mexican workers in the empirical distribution within regions. On average, five extra years of education for all Mexicans is needed to achieve an effect of a similar magnitude as with 1 year increase of schooling among Polish or Vietnamese workers. Moreover, such a large increase in Mexican workers schooling would affect 29 and 24 percent of comparisons with Vietnam and Cuba, respectively, while only 2 and 4 percent of rankings would be altered when Canada and China are considered. Similarly, 20 percentage points increase in the share of established migrants employed in the top sector in all regions still leaves all of the rankings with 10 out of 14 large countries unaffected.

Group's Placement in the Occupational Distribution

We now consider how the model would allocate 30 new migrants from each of the large sending countries. As above, we consider each country separately. For each group, in each region in which it has an established presence in 2011, we place 30 new migrants of this origin. The individual characteristics of these "extra" migrants reflect the distribution of individual characteristics in the whole sample in 2011 and is kept the same for all of the experiments. The "extra" workers are between 30 and 45 years old, ranging from no schooling to some college[22] and 65 percent of them speak good English. In each region the size of the of the network in the top and middle sector, arrival year and tenure in the region are predetermined by actual characteristics of given group in a region. We evaluate how new cohorts or immigrant workers would sort into the occupational distribution within regions. Since the individual characteristics are kept constant across groups and across regions within groups, the differences between the resulting location into occupational distribution highlights the role of the group's situation in the labor market in assessing the success of a new cohort. Table B.25 summarizes the results in terms of the shares of "extra" workers in the top and middle sector in selected regions. Overall, there appear to be less variation in terms of the shares of workers that would be allocated in the middle sector jobs. The shares in the middle sector vary between 17 and 60 percent but the majority falls in the 27-40 percent interval. In the top sector, however, the variation in the fraction of workers from each country of origin is bigger and varies between 3 and 53 percent. It is also not uncommon for groups to exhibit a large variation across regions. Workers from India, Africa and China display the biggest differences across regions. For example, in Riverside, CA 53 percent of the "extra" African workers would find

[22]Since our focus is on low skilled workers, the education composition is biased towards more individuals with at most high school degree.

employment in the top sector jobs, while in Philadelphia, only 3 percent would be employed in the top part of the occupational distribution . On the contrary, Mexican workers show the smallest variation across region with the share of the "extra" workers allocated in the top sector not exceeding 20 percent.

Examining each region separately reveals that within the same region workers from each group assume a different position in the occupational distribution. For instance, in San Francisco, while 40 percent of English, Canadian and German new workers would enjoy top sector jobs as a result of this experiment, only 27 percent of Russian, 20 percent of Chinese, Indian and Middle Eastern, 17 percent of Filipino and 10 percent of Mexican workers would find jobs in the top part of the empirical distribution. Given that individual characteristics are held constant across groups, these results highlight the role the group's success and history in the local labor market in the allocation of the future cohorts into the occupational distribution. It further stresses the importance of occupational hierarchies of immigrant workers and its implication for future generations of new immigrants.

Finally, note that despite the differences across regions for each of the country, it is clear that the "extra" workers from some countries, on average, are found in the top part of the empirical distribution more often than workers from other countries. On average over 25 percent of the "extra" Canadian, English, German and Middle Eastern workers finds employment in the top sector jobs while the same is true for less then 13 percent for Italian, Filipino, Vietnamese and Mexican workers. Of the groups that do not often find top sector jobs, workers from Vietnam and the Philippines appear to most often locate in the middle sector with, on average, 36 percent of the "extra" migrants employed in the middle part of the occupational distribution. Despite the relatively high shares of workers employed in jobs in the middle part of the occupational distribution, Vietnamese workers are among the groups with the highest average share of workers in the bottom sector, together with Polish, Italian and Mexican immigrants.

Ranking of New Groups

This previous section highlighted the differences in occupational distribution of new cohorts of immigrants. In reality though, it is unlikely that a region will receive an influx of immigrants from just one group. Moreover, looking at just one group at a time does not allow us to draw conclusions about the hierarchies among future cohorts of immigrants. Therefore, we now consider a large group of migrants from different origins arriving into the same region at the same time and analyze the resulting hierarchies among the "extra" workers".In each region, for each group with an established presence in 2011, we add 30 new migrants. As in the previous experiment, the distribution of individual characteristics is the same across groups and the characteristics capturing features of the country of origin are predetermined. The rankings are determined using average shares of workers in each of the sector. Since the distribution of individual characteristics of the "extra" workers is the same across groups the resulting ranking reflects the differences in the characteristics describing the origin of workers. Table B.26 summarizes the fraction of the "extra" workers employed in the top, middle and bottom sectors for selected regions. For each region we list all the groups that have an established presence and we sort the countries according to the share of the "extra" workers that would find jobs in the top part of the occupational distribution. As suggested in the previous experiment workers from certain countries, regardless of location, always rank first in the top sector (and last in the bottom sector). Specifically, workers from Canada, England, and Germany always exhibit the largest shares of workers in the top sector and the smallest share in the bottom sector. Mexican, Vietnamese and often African workers rank last in the top sector and first in the bottom sector. In all regions, more Chinese than Filipino workers find top sector jobs. India, Korea and China assume similar position in empirical distribution of occupations across regions, with the exception of New York, where Indian workers are not doing as well as Chinese and Korea workers.

One explanation for such persistence in the rankings is that even though the individual characteristics are the same across the "extra" migrants, the fact that we are considering a relatively low skilled future cohort affects the distribution in the occupational distribution. Thus, table Table B.27 summarizes the results of this experiment for a more skilled cohort of new migrants. Schooling still varies from 9 to 14 years but the share of immigrants with some college is higher than before (60 versus 30 percent). The results provide additional evidence that there is remarkable persistence in the rankings in regional labor markets. Even though it is often the case that the shares of workers employed in the top and middle sector are higher in the more skilled cohort almost all the hierarchies between groups are preserved. For example, in Dallas, TX, Orlando, FL, Minneapolis, MN and Columbus, OH, the occupational hierarchy remains unchanged. Only Polish workers in Chicago appear to improve their position significantly with higher average schooling. In Philadelphia, workers from the Philippines and China slightly improved their position while in San Francisco Indian workers benefit form the increased educational attainment in terms of their relative position in empirical distribution of occupations.

1.6 Conclusions

This paper provides clear evidence of a persistent hierarchical structure among immigrant labor groups in the United States with respect to their location in the occupational distribution of immigrant labor. Moreover, the evidence suggests that the hierarchy is not the result of immigrants sorting into occupations on the basis of specific immigrant groups having skills which assign them to occupations. Rather, the data indicate that the employers in labor markets at the metropolitan region level rank the workers partially on the basis of which immigrant group they belong and then assign the higher ranked workers to the better occupations. The evidence from estimation of a structural model in which employers rank workers according to their perceived productivity suggests the effect of membership of a particular immigrant group operates through immigrant networks. The presence of these network effects is largely responsible for the hierarchy persisting across regions and time.

Our empirical evidence is important not only because we are the first to document the existence of a persistent hierarchical structure among immigrant labor. It is also important because it highlights that the persistence we uncover is due to network effects. This clearly has implications for future generations of immigrants as the evidence suggests that those coming from specific countries will be disadvantaged in the United States labor market. This lack of a level playing field has implications for public policy. Moreover, given the recent evidence documenting the lack of intergenerational mobility with respect to movement in the income distribution (see for example, Chetty et al. (2014)) it is clear that the starting point for new immigrants has implications for their offspring and beyond.

Chapter 2

Ethnic Capital and Intergenerational Transmission of Educational Attainment

2.1 Introduction

Intergenerational transmission of human capital has been long studied in the literature with the primary focus on the link between parents and children schooling. With the growing importance of immigration around the Western world, the role of ethnicity in intergenerational transmission of education gained lots of attention. The "melting pot hypothesis" (Nathan and Moynihan, 1963) did not prove to be the correct model describing the assimilation of immigrants. It was replaced with various theories based on multiculturalism stressing the heterogeneity of the US society and prevalence of cultural and ethnic differences. Intergenarational linkage of skills can have long term effects on the socioeconomic status of an ethnic group in a destination country as well as on welfare distribution. Mejía and St-Pierre (2008) show that, just like differences in credit constraints, differences in endowment of the factors that complement schooling generate differences in human capital accumulation. More inequality in the complementing factors leads to a lower overall educational attainment. As a result, inequality might increase over time as both improvement among disadvantaged groups and dissemination of skills among more advantaged groups are slowed down.

The interplay between parental investments and environment also play a role in intergenerational transmission. On one hand, Bisin and Verdier (2001) find that parental investments and environment act as substitutes in the development of identity. On the other hand though, Patacchini and Zenou (2011) show complementarity between environment and parental investments in human capital formation process. The role of parents in facilitating ethnic socialization appears especially important given that ethnic minorities often face different developmental environment to majority youth (for a exhaustive summary of research see Hughes et al. (2006)). In light of these findings, it is natural to recognize the role of ethnicity in the complementing factors in human capital process accumulation.

? pointed to a distinct feature of intergenerational transmission among immigrants which he called transmission of ethnic capital. The overall human capital gained by the group as a whole is expected to have an effect on members of a group. Ethnicity is assumed to create an externality in the human capital accumulation process. The skills of the next generation depend on parental human capital and on the quality of ethnic environment in which parents make their investment decisions. It is expected that the social environment matters for educational choices and that social interactions play an important role in determining labor market success.

Borjas finds a strong evidence confirming the importance of the ethnic capital in human capital accumulation in the children's generation. Children's education attainment, occupational standing and earnings are affected not only by parent's education, occupational prestige or earnings but also by the average education or earnings of their corresponding ethnic group. However, Bauer and Riphahn (2007) found no evidence supporting Borjas's hypothesis using 2000 Swiss census data. Similarily, Aydemir et al. (2008) did not confirm the importance of ethnic capital in Canada and Nielsen et al. (2003) does not find a convincing evidence in Denmark. Moreover, more recent papers, including Borjas (1995), found that much of the ethnic capital is attributed to neighborhood effects (see for example Ioannides (2002) and Ioannides (2003)).

Given these different results, this paper aims to revise Borjas empirical framework which suffers from a significant limitation that undermines validity of the results. The two main regressors, parental and ethnic capital are likely to be endogenous and therefore they cannot be consistently estimated without appropriate corrections. Transfer of unobservables play a significant role in determining educational choices and exclusion restrictions proved to be difficult to find. Farré et al. (2013) find that a large part of the intergenerational education correlation, between parents and children, is due to the unobserved ability. This result suggests that in Borjas's analysis both the effect of parental and ethnic capital are likely to be overestimated.

To verify the extent to which unobservables confound the estimates, I apply an estimation procedure developed by Klein and Vella (2010), which allows estimation of the effect of parental and ethnic capital on education level without the necessity of having exclusion restrictions. Identification in the model relies on heteroskedasticity (see Klein and Vella (2010) for details). Therefore, effects of both parental and ethnic capital can be identified even without the appropriate instruments. This method has been successfully applied to estimate the intergenerational transmission of education in the US (Farré et al., 2013), to estimate returns to schooling in the US (Farré et al., 2011) and in Germany (Saniter, 2012), and also to estimate the occupational mobility in China (Holmlund et al., 2011; Emran and Sun, 1988).

I find evidence of an upward bias on both parental and ethnic capital of the OLS estimates. I also find evidence that while the effect of parental capital is relatively stable over time, the effect of ethnic capital has declined and vanishes in the post 1990 sample. Moreover, I find significant differences between men and women indicating that ethnic capital operates only trough women and have a negligible effect on education transmission among men. This suggest that the role of ethnicity differs by gender. Among others, this might reflect different socialization patterns and the effect of environment on educational outcomes of the youth.

The paper is organized as follows. The following section explains in detail the estimation method and identification. Section 3 describes the data and section 4 follows with empirical results and discussion. Section 5 concludes.

2.2 Model and Identification

In this section I follow Farré et al. (2013) and Farré et al. (2011) to describe the identification strategy and its interpretation in this framework. In the absence of exclusion restrictions, identification of the parameters relies on assumptions about the structure of the error term and heteroskedasticity in the model (see Klein and Vella (2010) for details). Let *edu* denote the individual's education, *eduf* the father's education and $e\bar{d}u$ the average education of the ethnic group (average education among immigrants from given country of birth in the parents generation). The model consist of three equations (for clarity of presentation no time identifier is included, so one should keep in mind that $e\bar{d}u$ represents the average education in the parents generation [1]:

$$
\begin{aligned}
edu_{ij} &= \gamma_1 eduf_{ij} + \gamma_2 e\bar{d}u_{ij} + \delta_0 X_{ij} + u_{ij} \\
eduf_{ij} &= \delta_2 X_{ij} + v_{ij}^{f} \\
e\bar{d}u_{ij} &= \delta_3 X_{ij} + v_{ij}^{av}
\end{aligned} \tag{2.1}
$$

[1] Average education in parents generation is computed as average education among the fathers within a cohort.

I assume that all variables in X are exogenous and that there are no instruments available for the two endogenous regressors. Exogeneity of X implies:

$$E(u_{ij}|X_{ij}) = E(v_{ij}^{f}|X_{ij}) = E(v_{ij}^{av}|X_{ij}) = 0$$

Since there are no variables that provide exogenous variation to identify the $\gamma's$, assume for simplicity that the same $X's$ appear in all three equations. In principle, they do not need to be the same. However, there is no source of exogenous variation to identify $\gamma's$ in equation 2.1. The variables that enter the parental or ethnic capital equations but do not appear in the primary equation do not grant identification. Detailed variables selection is discussed in the next section.

Furthermore, assume that the errors are heteroskedastic and can be defined as:

$$\begin{aligned} u_{ij} &= H_u(X_{ij})u_{ij}^{*} \\ v_{ij}^{f} &= H_v^{f}(X_{ij})v_{ij}^{f*} \\ v_{ij}^{av} &= H_v^{av}(X_{ij})v_{ij}^{av*} \end{aligned} \tag{2.2}$$

u_{ij}^{*}, v_{ij}^{f*}, v_{ij}^{av*} are correlated homoskedastic error terms and $H_u^2(X_{ij})$, $H_{v^f}^2(X_{ij})$ and $H_{v^{av}}^2(X_{ij})$ denote the conditional variance functions for u_{ij}, v_{ij}^{f} and v_{ij}^{av}. Each individual receives a transfer of unobserved ability, u_{ij}^{*}, v_{ij}^{f*}, v_{ij}^{av*}. This transfer is independent of the father's and child's environment as implied by equations 2.2. However, the heteroskedasticity implies that once we condition on the vector of exogenous variables X, the ability contributes differently to human capital accumulation depending on respective socioeconomic backgrounds [2]. Identification in the model is achieved through this variation. Without this variation the mapping from u^{*}'s and v^{f*}'s or v^{av*}'s is identical to the mapping between u's and v^{f}'s or v^{av}'s and therefore we

[2] This is one of the possible error structure and Klein and Vella Klein and Vella (2010) show that other structures are consistent with the constant correlation coefficient assumption.

cannot estimate the relationship between the u^*'s and v^{f*}'s or v^{av*}'s. In addition to the assumption of heteroskedastcity, the following constant correlation conditions are necessary for identification:

$$\begin{aligned} E[u_{ij}^* v_{ij}^{f*} | X_{ij}] &= E[u_{ij}^* v_{ij}^{f*}] = \rho^f \\ E[u_{ij}^* v_{ij}^{av*} | X_{ij}] &= E[u_{ij}^* v_{ij}^{av*}] = \rho^{av} \end{aligned} \tag{2.3}$$

This error structure implies that the correlation between the unobservables correlated with educational attainment are positively correlated with both parental and ethnic capital. This is consistent with the ability being responsible for the confounding effect of parental education and average educational attainment within the ethnic group. However, there is also a possibility that this correlation is negative. It would be the case if there were other unobserved factors that are not captured by ability. Examples of such factors are motivation, norms and beliefs. It is possible to extend the error structure to accommodate this case without compromising any of the identification in the model(Klein and Vella, 2010; Farré et al., 2011). However, since in this application I find a positive correlation, I will refer to the simple structure as in 2.3. Notice however, that the identification fails if there are factors that are related to the exogenous variables in the model and to the correlations between the unobservables that are not controlled for. In the context of this paper, the conditional constant correlation assumption implies that after controlling for all the exogenous variables in the model, the correlation between the unobservables factors affecting individual's educational attainment and parental educational attainment or average educational attainment in the ethnic group, remains constant. Therefore, the identification would fail if this transfer was affected by individual's behavior of environment. The heteroskedasticity implies that the contribution of the ability to the formation of educational attainment differ depending on characteristics.

To summarize, both heteroskedasticity and constant correlation between the homoskedastic error term in the child's equation and the father's or the ethnic capital equation are necessary for identification. Consider the latter condition first. If unobserved ability is transferred genetically, than this assumption is clearly satisfied. In case of parental capital, this approach was successfully applied in Farré et al. (2011) and Farré et al. (2013). In case of ethnic capital, literature delivers some evidence justifying this error structure. First of all, there is a plethora of research focusing on selection of immigrants. **?** points to the fact that not much can be inferred from a cross section about social mobility of immigrants due to a confounding effect of cohort quality. As migration decision is driven by a number of push and pull factors, the individuals that end up migrating from one country to another at a certain point in time are likely to be similar. This implies that unobserved individual ability correlates with unobserved characteristics of the ethnic group within the cohort.

Moreover, ethnic features are passed on genetically from the parents to the children. Bourdieu (1986) distinguishes between social and cultural ethnic capital. While the latter relies on group membership and networks, the former is enacted regardless of whether individuals are isolated or form a part of a community (Portes, 2000). This transfer goes beyond the transfer of unobserved cohort quality and includes norms and beliefs that originate in culture that is shared by an ethnic group. Cultural capital includes attitudes, norms, and skills that give an individual higher status in society (Portes, 2000) and its effect goes beyond peers effects.

Since parents can shape their children contacts with other ethnic group members, this ensures presence of heteroskedasticity in the error term of the primary equation-second condition required for identification. Borjas (1995) showed that neighborhood effects cannot account for the entire impact of ethnicity on intergenerational transmission of education, especially among less skilled individuals. Provided that individuals interact with other individuals from the same country of birth, ethnic capital effect goes beyond neighborhood effects. Borjas uses the following example to illustrate this point. Consider two immigrants identical in all respect, except from the fact that one comes from Korea and the other from Mexico. Even if both grow up in the same neighborhood, the Mexican child is more likely to interact with children of less educated parents, whereas the Korean is more likely to have friends with highly educated parents. The choice of the neighborhood in which a child grows up introduces heterogeneity to this effect, but, as empirical evidence shows, cannot erase it completely. The latter finding further supports the assumption that the transfer is constant regardless of environment or behavior. The previous confirms that the effect of the transfer can be modified by either behavior or environment.

In addition to peer effects, heteroskedacticty is granted by the fact that parents will invest less effort in child's education in favorable ethnic environment and more in less favorable (Bisin and Verdier, 2001). Therefore, negative (positive) effect of ethnic ability can be alleviated (reinforced) by shaping the child's interaction with other persons of the same ethnicity. Parents actions will, in turn, vary by their socioeconomic status as well as by their children characteristics. In contrary to Bisin and Verdier (2001), Patacchini and Zenou (2011) finds evidence of cultural complementarity of parental effort and quality of neighborhood. While among more educated parents, parental effort seem to be more influential than neighborhood effects, among low educated parents, neighborhood seem to play a significant role. Another source of heteroskedasticity comes from the finding that parents apply different ethnic socialization models to sons and daughters (Suárez-Orozco and Qin, 2006; Dion and Dion, 2001). Especially parents born outside of the US tend to have higher expectations for their daughters to embody home country cultural traits (Gupta, 1997). Moreover, as discussed in Farré et al. (2011), heteroskedasticity also arises due to regional differences in access to educational institutions as well as ethnic diversity. Also, the fact whether a parents were born outside of the US introduces additional variation as they do not have as good information about US educational system as parents that were born in the US.

Furthermore, selection into migration may lead to heteroskedasticity in the parental and ethnic capital. Depending on when and which country are the parents migrating from, they will be either positively or negatively selected and therefore the $H^2_{v^f}(X_{ij})$ and $H^2_{v^{av}}(X_{ij})$ will not be the same across individuals.

To summarize and give some more intuition consider two individuals coming from the same ethnic background and having identical parents, so that they receive identical transfers of ability, $v_i^{f*} = v_j^{f*}$ and $v_i^{af*} = v_j^{af*}$ but different observed characteristics X. The differences in $X's$ guarantee that the mapping between the v^{f*}, v^{af*} and u is not constant across individuals and thus identify the effect of parental and ethnic capital in educational attainment. In other words, the effect of this identical transfers on educational attainment of an individual varies with individual's characteristics. That means that the effect of coming from a background of low average ability or having parents of low ability can be influenced by parental investments such as choice of neighborhood or schools. Similarly, the effect of high ability parents or high average ability ethnic group can be diminished or increased by similar parental investments. The differences in educational attainment resulting from these differences in behaviors and environments across otherwise "identical" individuals grants us variation necessary to identify the relationship between the v^{f*}, v^{af*} and u.

This error structure allows construction of a control functions which inclusion in the main equation makes estimation of the unknown parameters γ feasible. This is done by inclusion of consistent estimates of v_{ij}^{av} and v_{ij}^{f} in the child's education equation. Let $\lambda_1 = \frac{Cov(u_{ij}, v_{ij}^f)}{Var(v_{ij}^f)}$ and $\lambda_2 = \frac{Cov(u_{ij}, v_{ij}^{av})}{Var(av_{ij}^f)}$. Then we can rewrite the error term u as:

$$u_{ij} = \epsilon_{ij} + \lambda_1 v_{ij}^f + \lambda_2 v_{ij}^{av} \tag{2.4}$$

Equation 2.4 explicitly shows why heteroskedasticity is necessary for identification. If all errors are homoskedastic the control function has the same impact across all individuals, i.e. λ_1 and λ_2 are constant. Let $A_1(x_{ij}) = \rho_1 * \frac{H_u(x_{ij})}{H_v^f(x_{ij})}$ and $A_2(x_{ij}) = \rho_2 * \frac{H_u(x_{ij})}{H_v^{av}(x_{ij})}$. Then, under the conditional correlation assumption in equation 2.3, we can rewrite the above error term as:

$$u_{ij} = \epsilon_{ij} + A_1(x_{ij}) v_{ij}^f + A_2(x_{ij}) v_{ij}^{av}$$

Given equation 2.3, both $A_1(x_{ij})$ and $A_2(x_{ij})$ are non linear in $x'_{ij}s$ and that grants us identification of the parameters of the child's education equation by estimating the following model:

$$edu_{ij} = \delta_0 X_{ij} + \gamma_1 eduf_{ij} + \gamma_2 ed\bar{u}_{ij} + \rho_1 * \frac{H_u(x_{ij})}{H_v^f(x_{ij})} v_{ij}^f + \rho_2 * \frac{H_u(x_{ij})}{H_v^{av}(x_{ij})} v_{ij}^{av} + \epsilon_{ij}$$

2.3 Data and Summary Statistics

I use 1977-2010 General Social Survey data. The sample consist of 14366 individuals aged 18-64 and born in the United States. I exclude individuals that were born abroad as well as native Americans and African Americans from the sample. Also, only individuals who grew up with both parents are included. Individuals for whom information about their own or their parents education attainment is not available are omitted from the sample. Individuals in the sample were born between 1913 and 1992 and they are divided into 4 different cohorts[3]. Also, only individuals for whom

[3]Data on parents age is not available so I use year of birth to categorize into cohorts. Finer division is not possible due to small cell sizes.

there is at least 30 other individuals in the same cohort coming from the same ethnic group are included [4]. Since data on father's education is available for more individuals in the sample I measure parental human capital with father's education and ethnic capital as the average education in the father's generation[5].

The final sample contains individuals coming from 32 different origins. First column of Table D.1 presents the breakdown by country or region of origin in the whole sample. Descendants of Germans, English, Welsh and Irish immigrants are most represented in the sample, while other origins constitute a small shares of the total sample. Table D.2 presents the summary statistics for all variables used in this analysis and it breaks it down by gender. The first three columns show the summary statistics for the whole sample, the fourth column for the sample used in Borjas's analysis (1977-1989) and the last column considers the post 1990 sample. Consider the full sample first. 53 percent of the sample are women. The average individual is about 40 years old, has about 3 siblings and has completed 14 years of schooling, which is surprisingly high. The average parental and ethnic capital are approximately the same at 11.5 years of schooling. 42 percent of all individuals lived in urban setting at the age of 16 and 25 percent lived in the South at the age of 16. Only 10 percent of individuals have at least one parent born abroad. The differences between men and women are very small, however the difference in years of self and average schooling within ethnic group is statistically significant at 1 percent significance level. Not surprisingly, in the sub sample until 1989, average educational attainment, among children, parents and

[4] This threshold is completely arbitrary and a higher threshold would be more desired. However, higher thresholds resulted in significant sample size loss and more importantly fewer ethnic groups.

[5] Due to the high correlation between father's and mother's education and since data on father's education was available for more observations, I only include father's education in the estimation. Moreover, Farre, Klein and Vella Farré et al. (2011) find that the high correlation between parent's education make it difficult to disentangle the effects of mother's and father's schooling.

ethnic groups is lower than in the whole sample. In the pre 1990 sample, an average individual and parent completed 13.4 and 10.8 years of schooling respectively. These numbers were 14.3 and 12.2 in the post 1990 sample. Also, individuals in the post 1990 sample are on average 3.5 years older and have less siblings.

Table D.3 presents the key variables, self, parental and average ethnic educational attainment by region of origin. Table D.4 presents the same information but breaks the sample by cohorts. There is a lot of variation in father's education and ethnic capital across different origins. Individuals of Russian decent and their fathers have the highest educational attainment throughout the years. In more recent years they are closely followed by the Chinese. Also, individuals of Indian decent born between 1950 and 1969 show exceptionally high self, parental and ethnic capital. Children of Mexican origin have the lowest educational attainment, although the gap has decreased over years. Nevertheless, their fathers are still ranked last and so is the overall ethnic capital. It is worth noticing though that the gap in the average education attainment decreased from about 6.2 years for individuals born between 1913-1929 to about 2.6 years among individuals born between 1970 and 1992. This decrease is partially driven by the large increase (about 4 years) in average schooling among individuals of Mexican origin. On the contrary, even though the average ethnic capital grew among all origins, the gap in the ethnic capital has remained relatively constant throughout the years.

Table D.5 presents the fraction of individuals obtaining at most high school or above high school education conditional on father's education or average education. I use 12 years of education as a dividing point. Since only 10 percent of all individuals have fathers born abroad it seems reasonable to assume it. While having a father who completed more than 12 years of schooling significantly increases chances that an individual will stay at school for more than 12 years, having a father who completed at most 12 years of schooling does not predict schooling in the children generation well. Out of individuals whose fathers have completed 13 or more years of education, only 16 percent completed 12 or less years of schooling. The remaining 84 percent followed their fathers and obtained at least 13 years of schooling. The probability of staying at school for more than 12 years is almost the same as finishing at at most 12 if a father completed at most 12 years of schooling. Similar, yet slightly less striking picture emerges from the lower panel. 66 percent of individuals coming from ethnic groups with relatively high average years of schooling end up staying at school for over 12 years. However, 54 percent of individuals coming from relatively low educated ethnic group end up obtaining more education then their counterparts in fathers generation.

The comparison between the pre- and post 1990 sample shows that in the latter, a much higher percentage of individuals whose fathers have at most high school education, obtained an above high school education. It is even more striking in the case of ethnic capital. Out of individuals coming from groups characterized by at most high school average education, 15 percent more obtained above high school education in the past 1990 sample in comparison to their counterparts in the pre 1990 sample. This difference could be driven by the general trend in the US population to continue education past high school.

2.4 Empirical Strategy

The summary statistics confirm the hypothesis that educational attainment of an individual is not only related to parental education but also to the average level of education among countryman in the father's generation. Now, let us turn to a more rigorous examination of the effect of parental and ethnic human capital. First, consider the OLS estimates of intergenrational transmission, which are presented in the first column of Table D.9. In line with existing literature, I find that each additional year of average and parental schooling increases the child's education by 0.108 years and 0.247 respectively. Both coefficients are significant at 1 percent level.

In order to account for endogeneity, one could argue that averages of exogenous variables can be used as instruments for the endogenous regressors. Even though it might be convincing in the ethnic capital case, it is hard to justify these instruments as valid exclusion restrictions for parental education. Another approach could be to use a mix of the classic control function and the conditional correlation coefficient methods. Both of these approaches resulted in counter intuitive results leading to a conclusion that in this case the conditional correlation coefficient estimator is the most appropriate.

I follow closely Farré et al. (2011) in the estimation strategy [6]. Since there are two endogenous regressors, father's education and ethnic capital, I first estimate these two equations using OLS and get the residuals. Next, the conditional variance in both equations is estimated using non linear least squares. I use exponential function to model the conditional variance in all equations. The last step involves simultaneous estimation of the heteroskedastic index and the coefficients of the main equation. This is obtained by standard iterative procedure. I start with a guess of coefficients for the main equation (OLS estimates). Then, given these coefficients I compute residuals and estimate the heteroskedastic index of the main equation. Given these estimates, I improve the guess of coefficients by including this correction term into the equation and estimating it by OLS to get new set of coefficients. This process continues until the coefficients values converge.

[6] Details of estimation are explained in Appendix C.

Parental and Ethnic Capital Equations

The sets of variables included in the parental and ethnic capital equations are almost the same, so I discuss them together. Since I do not have information about the age of the parents, I include the age of the children (and age squared) in both of the equations. This, together with the dummy variable indicating the cross section, control for the age of the fathers and the generation from which they are coming from. Dummy variables for regions control for geographic differences in educational attainment that might result from labor market specific needs of given region or different access to educational institutions. I also include a dummy variable indicating whether the child was living in the south or in the city at the age of 16. Unfortunately, this information is not available for the parents so I use the information for the children as proxies. In the ethnic capital equation I also include a dummy indicating whether at least one of the parents is foreign born and in the father's schooling equation a dummy variable indicating whether the father is foreign born.

The OLS result presented in the first two columns of Table D.6 are in line with the literature. All the year dummies (with the exception of 1978) are significant and indicate an increasing trend in educational attainment among parents. Younger individuals and those with fewer siblings have not only better educated father's but also more favorable ethnic environment. Individuals who were living in the city at 16 also have better educated parents. At the same time, they seem to be exposed to lower ethnic capital then their counterparts residing outside of the cities. However, the coefficient is insignificant. Residence in southern states doesn't seem to affect average education within ethnic groups, but it lowers the average educational attainment of the fathers by approximately 0.75 of a year. Fathers born outside of the US have on average 2.4 years less of schooling than US born fathers. Also, average ethnic capital decreases for individuals with at least one parent born abroad. This might reflect the fact that more recent immigrant groups are on average less educated than members of established groups within the US. There is also some evidence of regional differences for both parental and ethnic capital.

Lower panel of Table D.6 presents the test statistics for White and Breush-Pagan tests for heteroskedasticity in both equations. The null hypothesis of homoskedastic errors is strongly rejected in both equations confirming presence of heteroskedasticity in parental and ethnic capital equations necessary for identification.

Having established presence of heteroskedasticity we can continue with estimation of its form to be able to construct the two control variables. In the paper results using the preferred specification are discussed. Table D.10, Table D.11 and Table D.12 show corresponding results with all variables entering the heteroskedastcity index. The results are qualitatively unaffected by the choice of the form of heterskedasticity. However, some small quantitative differences are present.

Results of the non linear least squares estimation of the conditional variance are presented in first two columns of Table D.7. Given the assumed exponential form of heteroskedasticity, I can directly interpret the coefficients. Older individuals are exposed to a smaller variation in average education among immigrants from the same origin as well as their fathers have smaller residual variance. This could result from increasing heterogeneity of immigrants coming form the same origin as well as increased access to education. Moreover, I find higher dispersion in fathers' education for individuals who lived in the city or in the south at the age of 16. Similarly, fathers born abroad and with more children have a higher variance in educational attainment. I also find bigger dispersion in ethnic capital for individuals with at least one parent born abroad. There is also some evidence of regional differences in the ethnic capital equation.

Education Transmission Equation

Having estimated the heteroskedasticity indexes for the two endogenous equations, I can now turn to estimation of the main equation. To construct the correction terms I still need the estimates of the heteroskesdticity index in the primary equation. These are estimated simultaneously with the coefficients of the main equation. As in the case of parental and ethnic capital Table D.8 presents results with the most preferred specification of the form of heteroskedasticity. Table D.11 shows results with all exogenous variables entering the conditional variance estimation. I find that women, younger individuals and individuals with more siblings have a smaller residual variance.

Now, turn to the most important results of this paper. Table D.9 presents the OLS and control function (CF) estimates of the primary equation. Consider the first two columns first. Of biggest interest are the differences between the OLS and CF estimates on the parental and ethnic capital. I find that accounting for endogeneity reduces the coefficient on father's education from .25 to .19 and from .11 to .05 on ethnic capital. This confirms the fact that OLS coefficients are confounded by the endogeneity of parental and ethnic capital. The coefficients on control functions are both statistically significant at 1 percent significance level confirming the importance of unobserved ability and implying that the strategy employed in this paper is successful at capturing the endogeneity of parental and ethnic capital. Moreover, coefficients on both control functions are positive which confirms the conjecture that the unobservables are positively correlated across generations and justifies the interpretation of the assumed error structure. The magnitude of the effect of unobserved ability is similar to the one found by Farré et al. (2011).

However, I still find an important effect of father's education as well as I find evidence that ethnic capital plays a role in intergenerational transmission beyond the transfer of unobserved ability, even though not controlling for endogeneity results in a non trivial upward bias on both parental and ethnic capital coefficients. The effect of the unobserved ability is much stronger in case of the father's education. This can reflect the fact that unobserved ability transmitted through ethnic capital is more diluted as it reflects the average of the whole group.

I also find that individuals with more siblings and women have lower educational attainment. Similarly, individuals who lived in the south at the age 16 have acquired less years of education. Interestingly, individuals with at least one parent born outside of the US have higher educational attainment. This could be a result of the importance that immigrants place on education (Portes and Zhou, 1993). Notice also, that the OLS coefficient on at least one parent born abroad is almost twice as large as the coefficient in the CF approach. This confirms the argument of positive selection of immigrants and confounding effect of ability on parental migration dummy. Living in the city at the age of 16 increases educational attainment. I also find that age has a positive effect indicating that older individuals obtain higher educational credentials.

Pre and Post 1990 Results

In order to contrast the results in the whole sample with Borjas results, I estimate the model using the same sample, period between the years of 1977-1989 and contrast it with the results for post 1990 sample. OLS estimates for parental and ethnic capital and estimates for heteroskedastic indexes for parental, ethnic and child education are presented in the last columns of Table D.6, Table D.7, Table D.8. There is very small difference in the estimates of the conditional means for parental and ethnic capital (Table D.6). Only the effect of having a father or at least one parent born abroad differs significantly between the two samples. It is much smaller in case the post 1990 sample. This might reflect the fact that children of parents born abroad are facing more equal opportunities in terms of access to schooling in the later years. Similarly, in the estimation of the heteroskedastic indexes in the ethnic capital equations the role of having a at least one parent born abroad has decreased significantly.

Consider now the estimates of the main equation in the sub sample until 1989 and after 1990 presented in Table D.9). Already the OLS estimates show that the effect of ethnic capital has declined in the newer sample. The coefficient drops from 11 to 8 percent in the 1990-2010 sub sample but remains statistically significant. However, controlling for endogeneity of both parental and ethnic capital reveals that the effect of the latter becomes not only negligible but also insignificant. The CF estimates in the pre 1990 sample suggest that ignoring endogeneity results in a small upward bias but still shows that the effect of ethnic capital has a relatively large and significant effect on the intergenrational educational transmission. However, in the post 1990 sample, while OLS suggest a smaller but still significant effect of ethnic capital, in the CF estimates the effect of ethnic capital vanishes completely.

One of the reason why we observe such a drastic decrease in the role of ethnic capital could be the shift in the sample composition. However, as shown in Table D.1 there is very small change in the composition in terms of countries of ancestry and similarly, no significant changes are found in terms of basic characteristics of individuals as seen in Table D.2. Another factor that could contribute to this shift in the effect of ethnic capital is the increased diversity of immigrants coming from the same countries as well as bigger presence of migrants in general. Notice, that in the sample considered in this paper the fraction of individuals with at least one parent born abroad is very small (only 10 percent) and it has not changed over time. The fraction of immigrants in the population of the US has increased significantly between these two sub samples considered. Higher presence of immigrants may dilute the effect of each individual group similarily to the increased diversity of quality of immigrants from the same destination. Notice that in the estimation of the conditional mean of the ethnic capital presented in Table D.6 the effect of having at least one parent born abroad is almost 10 times smaller in the sub sample between 1990 and 2010. This can be driven by the increased quality of immigrants within some countries of origin over time. More detailed measure to capture the whole distribution of education within ethnic groups rather than just the mean is required to see if this is the case. Moreover, the lack of detailed geographic location makes the measure of both ethnic capital imprecise and the precision decreases with increased presence and diversity of immigrants. That is surely a limitation of this paper.

Moreover, notice that the decreasing effect of ethnic capital is seen already in the conditional probabilities of obtaining above HS education presented in Table D.5. Between 1977 and 1989 56 percent of individuals coming from ethnic groups with an average of above high school obtained above high school degree. This number was at 71 percent between 1990 and 2010. However, out of individuals with average ethnic capital of at most high school degree, 47 percent obtained above high school between 1977 and 1989 and 62 percent between 1990 and 2010. In the newer sub sample, the role of ethnic capital seem to be much smaller and the percentage of individuals who obtain above high school education is less dependent on high quality ethnic background.

Similarly, as discussed in the introduction, other authors also did not find an effect of ethnic capital and all these studies were conducted using resent years Bauer and Riphahn (2007); Aydemir et al. (2008); Nielsen et al. (2003).

In addition, I find a bigger effect of parental capital in the post 1990 sample, as the coefficient increases from .17 to .21. In both cases the coefficient on parental education is non trivially overestimated. The coefficients on the two control terms, ρ_1 and ρ_2 in both samples are positive confirming the role of unobserved ability in intergenerational transfer of educational attainment. Interestingly, the effect of unobserved ability in parental education decreased by almost a half in the newer sub sample and the effect of unobservables in ethnic capital effect on educational attainment doubled. In case of ethnic capital this result could indicate an increased selection among immigrants along unobservables in later years. The decreased role of parental unobserved ability could reflect easier access to educational institutions.

As far as other variables are concerned, as in the case of the estimation over the whole sample, the effect of having at least one parent born abroad is significantly overestimated with OLS. Also, its effect is almost twice as strong in the newer sample. This could be happening due to an increased positive selection in the post 1990 sample. Also, the share of immigrants of Chinese decent in the new sample is almost three times as large as in the sub sample until 1989 and there were no immigrants of Indian decent in the latter. Recent immigrants from these countries tend to be highly educated and place a significant role on education of their children. However, both groups constitute a very small percentage of the whole sample so it is rather unlikely that this is what driving this result. I also find a much stronger result for gender dummy indicating the bigger gap between men and women education attainment in earlier years. In fact, this gap vanishes in the newer sample. Also, living in the south at the age of 16 played a bigger role in the sub sample until 1989, which might reflect bigger constrains in access to universities and colleges.

Ethnic capital and gender

Since the literature delivers some evidence that ethnicity can have different impact on men and women I also investigate whether there is a difference between the transmission of ethnic capital for women and men. There are no major differences in the estimation of the conditional means with the whole sample as well as between men and women as seen in Table D.13. Table D.14 show that living in a southern state or in a city at the age of 16 and having siblings have a bigger effect on residual variance of the parental education attainment for men than for women. On the contrary, having a father born abroad has a bigger effect on women. Similarly, having at least one parent born abroad increases the residual variance of the ethnic capital among women significantly more than among men. Table D.15 shows the results for the heteroskedastic index in the main equation. It shows that number of siblings has a much stronger effect on the variation of educational attainment on women than it has on men.

Last but not least, consider the results of the main equation shown in Table D.16. OLS and CF estimates shows that living in a city at the age of 16 and having a foreign born parent have a stronger positive and significant effect on schooling among men. Just like in the whole sample, the CF estimates point to a smaller effect of parents born abroad for both men and women. Also the difference in the effect between men and women decreases once unobservables are accounted for.

I also find that while the direct effect of parental capital is stronger among women, the unobserved ability plays a more important role in the transfer among men. Both results point to a different pattern as in Farre et al. Farré et al. (2011). The authors find that while the direct effect of mother's education has a strong positive effect on daughters education, it does not play a role in son's education. On the other hand, father's educational attainment seem to play a much stronger role among sons. However, the overall effect is almost the same for both sons and daughters. The effect of the unobserved ability from fathers is of similar magnitude, however, the effect of the transfer of ability from mothers is almost twice as large for sons. The overall effect though is again almost the same across sons and daughters. This difference might occur due to the fact that I am not directly controlling for both fathers and mothers education and therefore, despite the positive matching, some of the information is lost. The correlation between fathers and mothers years of education in the sample is 0.63, which is lower than in Farre et al Farré et al. (2011). It could also be that in my estimation I am mostly picking up the effect of mother's years of education in which case the coefficients show a similar pattern. This pattern could also reflect the fact that for women it is the gender roles that matter more that actual ability. Mother's education has a much stronger direct effect on daughters than on sons, whereas, among sons the actual ability matters more for educational attainment.

Most importantly, consider the estimates of the ethnic capital. Already the OLS estimates reveal that ethnic capital has a very different effect among men and women indicating a stronger effect among women. CF estimates show that while the effect of unobserved ability is only slightly weaker for men, the direct effect of ethnic capital among men is much weaker and insignificant. This effect can also be related to the gender roles in ethnic groups. Table D.17 confirms the results obtained from the two sub samples and shows that once gender is interacted with ethnic capital, the coefficient on ethnic capital is negative and marginally significant. Notice that OLS estimates already reveal that the effect of ethnic capital differs between genders. The coefficient on the interaction term though is positive and significant indicating that ethnic capital affects the intergenerational transfer of education only among women. Notice also, that the difference in educational attainment between men and women disappear for highly educated ethnic groups (at least 13 years of average schooling). This confirms the importance of gender roles in determining the educational attainment.

The differential effect of ethnic capital among men and women might also result from distinct socialization patterns. Ethnic socialization, a concept that describes maturing to ethnic identity, has been recognized to vary significantly between boys and girls. Since, in general, girls are more susceptible to social influences, they might be more likely to be isolated due to parental fear of the "bad" influence of the majority. Therefore, girls are prone to a much stricter control over their brothers (Sung, 1987; Olsen, 1997). This finding is consistent over time and across almost all ethnic groups ((Dasgupta, 1998; Gupta, 1997; Williams et al., 2002; Yung, 1999; Sung, 1987)). As a result, girls might be more likely to have contacts with peers of the same ethnicity than their brothers. Moreover, such an increased supervision has proved to have a positive effect on schooling among Vietnamese girls (Zhou and Bankston III, 2001). Also, this could lead to a stronger importance of gender roles within ones ethnic group. High correlation between parental education implies that high average education within ethnic group is directly related to a high average education among women within this ethnic group. This could explain why average quality of ethnic group affects girls educational attainment but has no significant effect on boys. Even though girls are also more likely to rebel against the traditions and values, they have been found to be more flexible in choosing ethnic identity and building more complex ethnic identity by bridging home and host country identities (Rumbaut, 1997; Olsen, 1997). Girls have also higher educational and career aspirations, while boys tend to express more concern about social mobility (Suárez-Orozco and Qin, 2006). Also, boys are more pressured to take on their ethnic identity and are more likely to see the host country as hostile and unwelcoming (Suárez-Orozco and Qin, 2006). This might result in low self esteem and low aspirations and, therefore, boys might perceive a more limited set of opportunities in comparison to girls (Qin-Hilliard, 2003) regardless of the socioeconomic position of their ethnic group.

2.5 Conclusions

I find an evidence that the OLS estimates of the effect of ethnic capital on intergenerational transmission of education are biased upwards. Unobserved ability has an important effect on educational choices and not accounting for its confounding effect biases the estimates of parental and ethnic capital. I deliver new evidence on how ethnic capital contributes to the intergenrational transmission of educational attainment. I partially confirm Borjas's theory on a larger sample and also find that while the effect of ethnic capital was larger between 1977-1989, in the post 1990 sample the effect vanishes. This might reflect the affirmative actions and increased social acceptance of immigrants which could lead to less segregation and therefore smaller importance of one's ethnic group in determining schooling outcomes. I also find that while girls seem to benefit from their group's position, boys seem to be not affected in a significant manner.

In this paper I have established a link between ethnic capital and education of individuals, however I cannot say much about the mechanisms of transmission that go beyond the transfer of ability. Therefore, further research in this area should focus on possible channels of transmission. Moreover, this paper suffers from two significant limitation. First one was mentioned before and concerns the lack of detail geographic information. Second issue is related to the sample composition. The sample is biased towards individuals of European decent and 90 percent of individuals have parents who were already born in the US. Intuitively the contribution of ethnic capital to the intergenerational transmission of education should be stronger among individuals whose parents were born outside of the US. Also, given the changing scene of the immigration in the US, it would be desirable to have more of recent immigrants, such as migrants from South America and Asia. A consequence of this sample composition is a relatively high average schooling of ethnic groups which is not representative for the US population.

Another drawback of this research is a relatively small sample size by country of ancestry. Recall that I have included all individuals for whom there are at least 30 other individuals from the same country of origin in the same cohort. Increasing this threshold would increase the precision of using the means of education within a cohort within an ethnic group as a measure of ethnic capital.

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Appendix A

Estimation of the Covariance Matrix of Indirect Inference Estimator

The following appendix describes the estimation of the covariance matrix of the indirect inference estimator as explained in Appendix 1 and 2 of Gourieroux et al. (1993).

From Proposition 3 in Gourieroux et al. (1993), we know that:

$$\sqrt{N}(\hat{\beta_{MN}}(\Omega) - \beta_0) \xrightarrow{d} \mathcal{N}(0, W(M, \Omega))$$

where N denotes the sample size, M denotes the number of simulations, Ω denotes the weighting matrix and:

$$\begin{aligned} W(S,\Omega) &= (1+\frac{1}{S})\left[\frac{\partial b'}{\partial \beta}(\beta_0)\Omega\frac{\partial b}{\partial \beta'}(\beta_0)\right]^{-1}\frac{\partial b'}{\partial \beta}(\beta_0) \\ &\times \Omega\Omega^{*-1}\Omega\frac{\partial b}{\partial \beta'}(\beta_0)\left[\frac{\partial b'}{\partial \beta}(\beta_0)\Omega\frac{\partial b}{\partial \beta'}(\beta_0)\right]^{-1} \end{aligned}$$

where $b(\beta)$ denotes the binding function, β_0 denotes the true parameter values and $\Omega^* = J_0 I_0^{-1} J_0$ is the optimal weighting matrix.

To proceed with the estimation of the covariance matrix, we need to introduce some more notation. Let Q_N denote the objective function of the auxiliary model and:

$$\tilde{\theta} = \underset{\theta \in \Theta}{\operatorname{argmax}}\, Q_N(y, x, \beta)$$

Let $\hat{\theta}$ denote the estimates of the auxiliary model on the actual data. In our model Q_N is a block diagonal matrix, with diagonal elements equal to $-e'_{oj}e_{oj}$, where e_{oj} denotes the residuals from an OLS corresponding to j^{th} group in o^{th} sector [1].

From Appendix 2 of G we know that J_0 can be consistently estimated by:

$$-\frac{\partial^2 Q_N}{\partial\theta\partial\theta'}(y, x, \hat{\theta})$$

In our model, the above approximation becomes a block diagonal matrix with diagonal elements equal to $2x'_{jo}x_{jo}$. The middle term in the expression of Ω^*, $(I_0 - K_0)^{-1}$, can be consistently estimated by:

$$\frac{N}{S}\sum_{s=1}^{S}(W_s - \bar{W})(W_s - \bar{W})'$$

Where:

$$\begin{aligned} W_s &= \frac{\partial Q_N}{\partial\theta}(y^s(\tilde{\beta}), x, \hat{\theta}) \\ \bar{W} &= \frac{1}{S}\sum_{s=1}^{S} W_s \end{aligned}$$

and $\tilde{\beta}$ denotes a consistent estimator of β. S denotes the number of simulations in the estimation of $\tilde{\beta}$. Notice, that the optimal indirect inference estimator requires that we can get a preliminary consistent estimator β in order to get a preliminary estimate of the optimal weighting matrix. We can obtain these estimates using identity matrix as a weighting matrix.

In our model, W_s can be expressed as block diagonal matrix, with diagonal elements equal to $2x'_{jo}y_{jo}(\tilde{\beta}) - 2x'_{jo}x_{jo}\hat{\theta}$. In practice, we first estimate the model using identity matrix as weighting matrix and obtain $\tilde{\beta}$. Using $\tilde{\beta}$ we compute $y^s(\tilde{\beta})$ and obtain the matrix of first derivatives of the auxiliary model criterion function w.r.t. θ, so the parameters of auxiliary model.

[1] The negative sign follows from the fact that OLS minimizes the sum of squared residuals.

The last element in the expression of the covariance matrix contains the derivatives of the binding function at the true value. It can be consistently estimated with:

$$\frac{\partial b}{\partial \beta}(\beta_0) = J_0^{-1}\frac{\partial^2 Q_\infty}{\partial \theta \partial \beta'}$$

which can be obtained by numerical derivation of $\frac{\partial Q_N}{\partial \theta'}[y(\beta), x, \hat{\theta}]$ w.r.t. β and evaluated at the $\hat{\beta}$.

Appendix B

Tables and Figures for Chapter 1

Table B.1: Sample composition by year 1940-2011

	1940	1950	1970	1980	1990	2000	2011
Canada	0.11	0.11	0.14	0.07	0.03	0.03	0.03
Mexico	0.01	0.04	0.15	0.32	0.41	0.46	0.43
Cuba	0.00	0.00	0.06	0.10	0.07	0.04	0.03
England	0.06	0.05	0.05	0.03	0.02	0.02	0.01
Italy	0.29	0.32	0.20	0.09	0.04	0.02	0.01
Germany	0.15	0.12	0.13	0.08	0.05	0.03	0.03
Poland	0.16	0.17	0.10	0.04	0.02	0.02	0.01
Russia	0.19	0.16	0.06	0.00	0.01	0.03	0.03
China	0.01	0.01	0.05	0.06	0.07	0.07	0.08
Korea				0.02	0.04	0.03	0.03
Philippines		0.00	0.03	0.07	0.08	0.06	0.07
Vietnam			0.00	0.01	0.04	0.05	0.05
India			0.01	0.04	0.06	0.09	0.11
Africa			0.01	0.02	0.03	0.04	0.05
Middle East	0.01	0.01	0.01	0.03	0.03	0.03	0.03

Table B.2: Sample composition by year 1940-2011: unskilled workers

	1940	1950	1970	1980	1990	2000	2011
Canada	0.11	0.11	0.12	0.05	0.01	0.01	0.00
Mexico	0.01	0.04	0.17	0.49	0.63	0.72	0.73
Cuba			0.07	0.05	0.09	0.04	0.04
England	0.06	0.04	0.02	0.01	0.00	0.00	0.00
Italy	0.30	0.33	0.27	0.13	0.05	0.02	0.01
Germany	0.15	0.12	0.12	0.06	0.01	0.01	0.00
Poland	0.17	0.17	0.11	0.05	0.02	0.02	0.01
Russia	0.18	0.16	0.05	0.01	0.01	0.01	0.01
China	0.01	0.01	0.04	0.05	0.05	0.04	0.05
Korea				0.01	0.02	0.01	0.01
Philippines			0.02	0.04	0.04	0.02	0.02
Vietnam				0.01	0.03	0.04	0.04
India				0.01	0.02	0.03	0.03
Africa				0.01	0.01	0.01	0.02
Middle East	0.01	0.01	0.01	0.03	0.02	0.02	0.02

Figure B.1: Distribution of different groups into Metropolitan areas

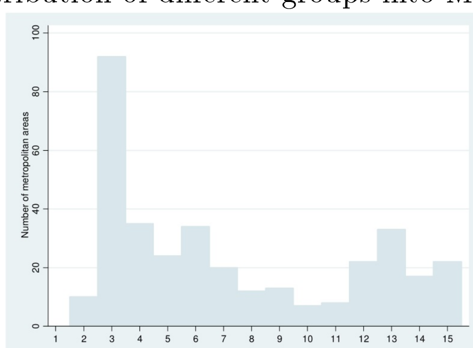

Table B.3: Summary statistics by country of origin by year 1940-2011

	Age	Edu	Eng	Net*	SEI	Age	Edu	Eng	Net	SEI
	Canada					**Germany**				
1940	42.90	9.52		0.49	34.04	45.35	9.17		0.47	32.74
	(12.83)	(2.71)		(0.12)	(21.54)	(12.15)	(2.60)		(0.05)	(20.69)
1950	44.58	6.64		0.54	37.52	48.49	6.60		0.53	37.48
	(11.68)	(2.97)		(0.10)	(22.67)	(11.05)	(2.81)		(0.03)	(21.58)
1970	45.78	11.41		0.60	43.65	45.35	11.44		0.57	43.33
	(13.54)	(3.00)		(0.09)	(24.02)	(14.98)	(3.09)		(0.05)	(23.46)
1980	43.68	12.65	0.99	0.66	48.39	39.99	12.75	0.99	0.63	47.39
	(14.52)	(3.13)	(0.08)	(0.09)	(24.84)	(13.67)	(3.19)	(0.09)	(0.08)	(24.69)
1990	42.07	13.84	0.99	0.73	52.00	40.65	13.77	0.99	0.65	48.80
	(13.12)	(2.35)	(0.08)	(0.08)	(24.34)	(13.20)	(2.30)	(0.08)	(0.09)	(24.83)

	Age	Edu	Eng	Net	SEI	Age	Edu	Eng	Net	SEI
2000	41.69	14.42	0.99	0.79	56.08	40.68	14.11	0.99	0.69	50.58
	(11.82)	(2.26)	(0.08)	(0.09)	(22.88)	(12.01)	(2.24)	(0.09)	(0.10)	(24.24)
2011	44.46	14.90	0.99	0.83	59.97	43.31	14.47	0.99	0.72	53.30
	(11.95)	(2.09)	(0.10)	(0.08)	(22.33)	(12.47)	(2.17)	(0.08)	(0.10)	(24.29)
	Mexico					**Poland**				
1940	38.71	7.70		0.14	18.15	47.53	7.28		0.34	28.29
	(10.16)	(2.81)		(0.00)	(16.47)	(9.91)	(2.54)		(0.04)	(21.00)
1950	44.15	5.65		0.17	20.31	52.48	5.86		0.38	31.25
	(10.42)	(1.80)		(0.02)	(16.81)	(10.39)	(2.13)		(0.09)	(22.14)
1970	36.80	8.58		0.18	22.10	51.34	10.26		0.49	39.40
	(12.98)	(2.83)		(0.02)	(16.36)	(11.58)	(3.25)		(0.09)	(23.20)
1980	32.71	8.76	0.48	0.20	22.50	49.09	11.21	0.84	0.48	39.21
	(11.49)	(2.93)	(0.50)	(0.05)	(16.93)	(13.43)	(3.33)	(0.37)	(0.13)	(24.08)
1990	32.40	9.35	0.52	0.20	22.27	43.84	12.62	0.76	0.43	36.80
	(10.72)	(3.05)	(0.50)	(0.04)	(17.39)	(13.01)	(2.78)	(0.43)	(0.08)	(24.56)
2000	33.68	9.79	0.50	0.21	22.89	41.39	12.96	0.74	0.39	34.91
	(10.86)	(2.86)	(0.50)	(0.05)	(17.57)	(12.22)	(2.40)	(0.44)	(0.08)	(23.11)
2011	38.32	10.25	0.52	0.23	24.10	43.61	13.40	0.78	0.43	37.61
	(11.37)	(2.89)	(0.50)	(0.05)	(19.43)	(12.53)	(2.28)	(0.41)	(0.08)	(24.67)
	Cuba					**Russia**				
1940						47.41	8.25		0.58	42.00
						(9.96)	(3.09)		(0.04)	(24.34)
1950	36.00	6.31		0.25	25.79	52.38	6.08		0.59	43.59
	(10.40)	(2.62)		(0.00)	(18.35)	(9.27)	(2.53)		(0.02)	(24.94)
1970	40.01	10.28		0.38	32.50	56.70	10.67		0.61	44.95
	(12.00)	(3.24)		(0.05)	(22.09)	(10.61)	(3.62)		(0.07)	(24.26)
1980	42.07	11.32	0.67	0.50	38.50	46.93	11.22	0.85	0.48	37.18
	(13.89)	(3.42)	(0.47)	(0.06)	(24.38)	(14.22)	(3.59)	(0.36)	(0.10)	(24.45)
1990	44.08	11.89	0.69	0.51	39.19	42.17	13.77	0.83	0.64	46.17
	(13.40)	(3.05)	(0.46)	(0.06)	(24.83)	(13.08)	(2.94)	(0.38)	(0.05)	(25.36)
2000	44.40	12.59	0.70	0.52	39.99	39.34	14.45	0.82	0.63	46.72
	(12.23)	(2.73)	(0.46)	(0.05)	(24.54)	(12.12)	(2.41)	(0.39)	(0.12)	(25.21)
2011	46.71	13.00	0.66	0.50	38.96	41.62	14.66	0.84	0.62	47.63
	(11.88)	(2.53)	(0.47)	(0.07)	(25.05)	(12.89)	(2.30)	(0.37)	(0.14)	(26.21)
	England					**China**				
1940	45.91	9.79		0.57	37.43	40.82	7.44		0.27	26.22
	(11.72)	(2.73)		(0.07)	(21.86)	(10.87)	(2.64)		(0.02)	(22.04)
1950	49.20	6.51		0.61	41.16	42.01	5.96		0.40	31.93
	(10.92)	(2.87)		(0.04)	(23.12)	(11.35)	(2.29)		(0.06)	(24.03)
1970	45.21	12.02		0.67	49.12	42.36	11.15		0.45	38.51
	(14.22)	(3.18)		(0.06)	(24.22)	(12.68)	(4.02)		(0.07)	(27.25)
1980	40.60	13.20	1.00	0.73	53.00	39.83	12.55	0.72	0.58	45.55
	(13.45)	(3.32)	(0.05)	(0.06)	(24.57)	(12.38)	(4.03)	(0.45)	(0.13)	(27.92)
1990	40.08	14.10	1.00	0.76	53.84	40.37	13.69	0.74	0.66	49.37
	(12.46)	(2.14)	(0.07)	(0.07)	(23.84)	(11.58)	(3.35)	(0.44)	(0.13)	(27.01)
2000	41.91	14.48	0.99	0.79	55.85	41.26	14.22	0.76	0.71	52.87
	(11.61)	(2.13)	(0.07)	(0.07)	(22.64)	(11.27)	(3.19)	(0.43)	(0.13)	(25.96)
2011	45.40	14.59	1.00	0.80	57.52	44.03	14.57	0.77	0.72	55.09
	(11.73)	(2.09)	(0.06)	(0.05)	(22.56)	(11.47)	(3.07)	(0.42)	(0.12)	(26.12)

	Age	Edu	Eng	Net	SEI	Age	Edu	Eng	Net	SEI
	Italy					**Korea**				
1940	46.14	7.18		0.28	25.23					
	(10.13)	(2.40)		(0.04)	(20.09)					
1950	50.91	5.59		0.31	27.55					
	(10.71)	(1.61)		(0.03)	(20.47)					
1970	45.59	9.24		0.29	29.36					
	(14.08)	(2.96)		(0.04)	(20.66)					
1980	43.49	10.37	0.84	0.37	33.68	37.59	13.65	0.69	0.62	46.33
	(12.69)	(3.21)	(0.36)	(0.05)	(22.90)	(10.05)	(3.45)	(0.46)	(0.10)	(25.46)
1990	46.00	11.37	0.89	0.44	37.94	39.23	13.95	0.70	0.69	48.53
	(12.20)	(3.15)	(0.31)	(0.07)	(24.53)	(11.65)	(2.50)	(0.46)	(0.09)	(24.48)
2000	48.19	12.31	0.93	0.50	41.32	41.24	14.39	0.72	0.73	51.65
	(11.16)	(2.95)	(0.25)	(0.09)	(24.84)	(11.90)	(2.35)	(0.45)	(0.07)	(23.91)
2011	51.07	12.97	0.95	0.57	45.64	44.12	14.93	0.76	0.77	55.80
	(11.20)	(2.82)	(0.22)	(0.08)	(25.81)	(11.56)	(2.12)	(0.42)	(0.06)	(23.44)
	Philippines					**Africa**				
1940										
1950	43.44	6.68		0.16	19.82					
	(10.55)	(2.93)		(0.00)	(20.18)					
1970	39.56	12.35		0.46	37.40	37.81	13.05		0.74	54.23
	(14.19)	(3.36)		(0.20)	(25.96)	(11.62)	(3.48)		(0.04)	(23.64)
1980	37.67	13.03	0.96	0.52	39.14	36.63	13.83	0.97	0.69	51.44
	(12.08)	(3.63)	(0.20)	(0.18)	(25.29)	(10.60)	(3.69)	(0.17)	(0.08)	(26.47)
1990	38.92	13.82	0.96	0.57	40.67	37.02	14.68	0.97	0.67	49.92
	(12.23)	(2.31)	(0.19)	(0.14)	(24.62)	(9.99)	(2.36)	(0.16)	(0.09)	(26.76)
2000	41.33	14.01	0.96	0.59	42.22	39.41	14.51	0.97	0.64	47.54
	(12.30)	(2.20)	(0.20)	(0.12)	(24.16)	(10.46)	(2.31)	(0.17)	(0.09)	(26.10)
2011	44.47	14.26	0.96	0.60	43.37	42.41	14.42	0.96	0.60	45.92
	(12.40)	(2.07)	(0.21)	(0.11)	(24.18)	(11.45)	(2.42)	(0.20)	(0.10)	(26.52)
	Vietnam					**Middle East**				
1940						42.14	9.03		0.50	38.51
						(9.70)	(3.30)		(0.00)	(23.91)
1950						50.72	5.94		0.55	41.11
						(9.40)	(2.38)		(0.02)	(24.74)
1970						42.55	12.18		0.68	49.00
						(14.98)	(3.73)		(0.04)	(24.59)
1980	32.14	12.18	0.73	0.49	39.15	36.08	12.39	0.91	0.64	47.99
	(10.67)	(3.25)	(0.45)	(0.08)	(23.98)	(11.81)	(3.62)	(0.29)	(0.08)	(25.62)
1990	34.18	12.69	0.77	0.53	39.91	37.95	13.46	0.95	0.69	50.26
	(10.54)	(2.76)	(0.42)	(0.09)	(24.40)	(11.41)	(2.89)	(0.22)	(0.08)	(24.91)
2000	38.23	12.75	0.73	0.50	40.32	39.50	13.75	0.94	0.70	51.29
	(11.19)	(2.86)	(0.44)	(0.08)	(24.83)	(11.12)	(2.75)	(0.24)	(0.10)	(24.62)
2011	43.77	12.98	0.73	0.52	42.60	43.02	14.14	0.95	0.72	54.20
	(10.92)	(3.05)	(0.45)	(0.08)	(25.55)	(11.62)	(2.67)	(0.22)	(0.11)	(24.35)
	India									
1940										

	Age	Edu	Eng	Net	SEI	Age	Edu	Eng	Net	SEI
1950										
1970	32.71	15.54		0.90	69.99					
	(6.84)	(2.97)		(0.00)	(21.76)					
1980	35.80	14.93	0.97	0.81	61.20					
	(8.67)	(3.33)	(0.18)	(0.06)	(25.23)					
1990	38.09	14.94	0.95	0.77	55.87					
	(10.53)	(2.52)	(0.21)	(0.08)	(25.35)					
2000	38.53	15.13	0.95	0.80	57.17					
	(11.36)	(2.44)	(0.21)	(0.10)	(23.47)					
2011	41.15	15.45	0.95	0.83	59.71					
	(11.67)	(2.26)	(0.21)	(0.10)	(22.19)					

Net denotes fraction of individuals employed in the top part of the occupational distribution

Table B.4: Share of workers in the top sector by region and year 1940-2011

	1940	1950	1970	1980	1990	2000	2011
			All workers				
Canada	0.72	0.69	0.64	0.65	0.66	0.76	0.76
Mexico	0.22	0.32	0.45	0.35	0.27	0.26	0.24
Cuba	0.64	0.50	0.53	0.59	0.57	0.57	0.56
England	0.64	0.73	0.67	0.63	0.67	0.72	0.71
Italy	0.49	0.48	0.44	0.53	0.55	0.61	0.66
Germany	0.59	0.67	0.59	0.56	0.60	0.65	0.68
Poland	0.53	0.54	0.55	0.56	0.60	0.65	0.62
Russia	0.76	0.73	0.59	0.49	0.69	0.63	0.59
China	0.56	0.65	0.65	0.71	0.68	0.74	0.74
Korea				0.59	0.58	0.69	0.74
Philippines		0.45	0.53	0.65	0.58	0.64	0.64
Vietnam			0.54	0.37	0.43	0.46	0.45
India			0.84	0.82	0.81	0.85	0.86
Africa			0.77	0.64	0.69	0.70	0.65
Middle East	0.71	0.57	0.73	0.64	0.71	0.74	0.76
			Unskilled workers				
Canada	0.75	0.69	0.67	0.72	0.73	0.76	0.75
Mexico	0.23	0.34	0.41	0.46	0.43	0.47	0.44
Cuba	0.54	0.50	0.43	0.61	0.59	0.64	0.60
England	0.66	0.72	0.71	0.71	0.73	0.75	0.79
Italy	0.52	0.49	0.52	0.61	0.64	0.74	0.69
Germany	0.58	0.66	0.62	0.64	0.68	0.74	0.74
Poland	0.58	0.53	0.55	0.63	0.67	0.70	0.67
Russia	0.78	0.74	0.73	0.49	0.66	0.68	0.60
China	0.49	0.65	0.44	0.50	0.50	0.51	0.51
Korea				0.57	0.63	0.69	0.70
Philippines			0.45	0.56	0.58	0.61	0.67
Vietnam			0.33	0.49	0.58	0.62	0.64
India			0.59	0.61	0.70	0.72	0.75
Africa			0.60	0.59	0.65	0.67	0.61
Middle East	0.72	0.59	0.59	0.67	0.71	0.73	0.77

Table B.5: Average prestige score by group and year 1940-2011

	1940	1950	1970	1980	1990	2000	2011
All workers							
Canada	41	42	46	48	49	53	56
Mexico	17	21	34	28	24	23	22
Cuba	38	36	43	46	44	44	43
England	36	44	47	47	49	50	52
Italy	27	29	34	41	42	44	49
Germany	33	37	43	42	44	46	48
Poland	31	33	42	44	46	49	48
Russia	46	45	44	40	50	47	46
China	42	44	52	55	53	57	58
Korea				47	46	51	54
Philippines			47	50	46	47	48
Vietnam				33	35	36	36
India			67	65	63	62	64
Africa			58	49	52	53	50
Middle East	42	39	55	49	53	53	57
Unskilled workers							
Canada	36	41	38	38	35	37	38
Mexico	15	21	24	22	19	19	19
Cuba	31	36	26	31	27	30	27
England	33	41	40	37	35	38	39
Italy	26	29	29	33	31	34	36
Germany	29	36	37	32	32	33	34
Poland	30	32	33	34	29	30	29
Russia	43	45	39	29	30	29	28
China	34	44	32	34	30	29	31
Korea				28	30	35	38
Philippines			27	28	25	27	29
Vietnam				25	24	25	25
India			41	37	36	36	37
Africa			39	34	32	31	28
Middle East	39	39	40	35	35	37	40

Table B.6: Occupational prestige distance by pair of countries over time

	15**	14	13	12	11	10	9	8	7	6	5	4	3	2	1
15*							6.7	-5.2	2.1	2.5	6.2	-0.6			-0.2
							6.6	-0.8	5.9	2.1	8.8	0.8	10.1		1.2
		-2.8	-14.7		3.8		4.8	0.4	4.0	2.4	10.8	0.2	9.0	18.1	1.5
		-1.1	-8.2	8.5	1.1	2.6	-1.1	5.7	4.6	1.3	8.9	-1.3	6.1	16.7	-0.2

	15**	14	13	12	11	10	9	8	7	6	5	4	3	2	1
		0.1	-4.4	10.4	2.5	1.5	-2.2	0.5	5.7	1.0	7.2	-1.3	4.8	18.6	-0.7
		2.0	-4.4	10.2	4.5	0.7	-1.8	3.3	6.4	0.7	5.7	-1.6	7.9	19.3	-2.1
		4.8	-4.4	9.2	5.9	-0.7	-2.1	4.1	8.5	1.2	4.7	-1.0	7.9	20.5	-2.6
14	1.1		-6.4	8.4	1.2	1.3	0.0	8.6	7.5	1.6	10.7	1.9	6.5	17.3	0.2
	-0.1		-4.2	7.0	3.1	-1.8	-2.7	1.1	7.4	0.4	8.6	-1.2	4.3	18.1	-1.8
	-2.0		-7.7	4.7	2.8	-5.8	-4.5	1.2	6.1	-1.6	4.8	-1.9	6.6	16.9	-4.4
	-4.8		-9.8		1.3		-7.4	-0.1	4.6	-3.4	1.0	-3.4	3.6	15.3	-7.3
	2.8		-9.0	8.8	6.7	2.4	7.6	4.6	5.5	4.9	13.9	-5.7	11.9	18.0	4.1
13	8.2	6.4		13.3	8.5	5.0	7.1	16.4	15.4	11.2	19.1	12.9	13.8	24.8	7.9
	4.4	4.2		14.4	6.9	4.4	1.9	4.5	11.2	6.4	12.8	6.7	8.8	22.0	3.6
	4.4	7.7		13.9	8.6	3.0	2.0	7.2	11.5	6.8	11.9	2.8	11.8	23.6	2.7
	4.4	9.8			9.4		1.9	8.2	13.2	6.4	8.9	2.2	12.0	23.8	2.2
	14.7	9.0		14.6	10.1	10.2	19.7	16.7	21.0	18.8	26.9	3.2	23.3	31.1	15.2
12	-8.5	-8.8	-14.6		-3.8	-4.3	-9.6	1.2	-4.1	-7.1	1.4	-10.8	-4.0	9.6	-9.2
	-10.4	-8.4	-13.3		-3.7	-6.3	-10.0	-8.0	-4.8	-8.3	-2.9	-11.5	-4.1	9.6	-11.2
	-10.2	-7.0	-14.4		-4.2	-8.3	-11.1	-5.2	-3.3	-9.0	-4.3	-11.3	-1.8	9.3	-11.5
	-9.2	-4.7	-13.9		-2.8	-9.8	-10.9	-4.9	-2.1	-8.8	-5.4	-10.3	-1.9	10.4	-12.3
11							-6.4	-16.3	-20.6	-14.2	8.8	-18.3		-1.1	-17.2
	-3.8	-6.7	-10.1				2.7	-0.1	4.5	0.5	7.4	-3.4	9.0	7.2	-4.3
	-1.1	-1.2	-8.5	3.8		-0.6	-3.3	9.7	6.0	-1.1	5.5	-3.7	5.6	13.6	-3.1
	-2.5	-3.1	-6.9	3.7		-2.1	-4.6	0.1	6.1	-2.7	2.3	-5.1	3.5	13.5	-5.5
	-4.5	-2.8	-8.6	4.2		-4.1	-6.4	-1.2	4.9	-4.3	-0.7	-6.6	3.9	13.7	-7.3
	-5.9	-1.3	-9.4	2.8		-6.5	-7.6	-1.8	4.6	-5.0	2.6	-7.1	2.3	13.7	-8.7
10	-1.5	-1.3	-5.0	6.3	2.1		-3.4	0.9	6.0	-1.3	6.8	-4.9	4.0	16.3	-3.8
	-0.7	1.8	-4.4	8.3	4.1		-2.4	2.9	8.9	-0.4	6.3	-4.0	7.6	18.9	-3.4
	0.7	5.8	-3.0	9.8	6.5		-1.3	4.7	8.4	1.2	4.7	-3.0	6.6	20.8	-2.9
	-2.6	-2.4	-10.2	4.3	0.6		-3.3	7.7	2.0	-1.7	5.9	-0.9	2.7	14.8	-4.0
9	-6.7							-8.4	-2.7	-4.1	1.3	-7.8			-10.5
	-6.6				6.4			-7.5	-2.8	-5.7	1.6	-7.4	3.5	5.5	-7.2
	-4.8	-7.6	-19.7		-2.7			-2.6	1.0	-3.1	6.6	-6.7	5.5	13.1	-2.6
	1.1	0.0	-7.1	9.6	3.3	3.3		8.4	5.6	2.5	10.6	-0.8	6.8	18.0	0.5
	2.2	2.7	-1.9	10.0	4.6	3.4		1.9	8.2	2.6	9.3	-0.3	7.0	19.9	-0.2
	1.8	4.5	-2.0	11.1	6.4	2.4		5.3	10.1	3.0	8.8	-0.5	9.8	22.0	-0.3
	2.1	7.4	-1.9	10.9	7.6	1.3		6.1	11.5	3.6	6.3	0.6	8.5	22.8	-0.3
8	5.2						8.4		8.8	5.0	11.1	3.1		18.4	1.7
	0.8				16.3		7.5		6.5	3.4	9.1	2.0	11.4	15.6	1.5
	-0.4	-4.6	-16.7		0.1		2.6		2.2	0.7	8.4	-2.1	7.6	14.4	0.1
	-5.7	-8.6	-16.4	-1.2	-9.7	-7.7	-8.4		-1.6	-6.7	2.8	-8.8	-1.7	8.4	-8.1
	-0.5	-1.1	-4.5	8.0	-0.1	-0.9	-1.9		4.8	-1.1	6.5	-3.6	5.5	16.4	-2.5
	-3.3	-1.2	-7.2	5.2	1.2	-2.9	-5.3		6.0	-3.5	4.4	-5.5	6.2	16.0	-6.7
	-4.1	0.1	-8.2	4.9	1.8	-4.7	-6.1		4.6	-3.9	1.6	-5.6	4.4	15.9	-7.8
7	-2.1						2.7	-8.8		-4.0	1.9	-5.3		6.5	-5.5
	-5.9				20.6		2.8	-6.5		-3.1	1.9	-4.7	6.3	13.0	-5.8

	15**	14	13	12	11	10	9	8	7	6	5	4	3	2	1
	-4.0	-5.5	-21.0		-4.5		-1.0	-2.2		-1.7	5.7	-5.2	6.8	11.2	-2.0
	-4.6	-7.5	-15.4	4.1	-6.0	-2.0	-5.6	1.6		-4.5	2.8	-5.3	1.4	12.2	-4.9
	-5.7	-7.4	-11.2	4.8	-6.1	-6.0	-8.2	-4.8		-5.7	1.3	-8.0	-0.4	11.5	-6.6
	-6.4	-6.1	-11.5	3.3	-4.9	-8.9	-10.1	-6.0		-7.0	-0.3	-10.0	-0.4	11.2	-9.4
	-8.5	-4.6	-13.2	2.1	-4.6	-8.4	-11.5	-4.6		-8.5	-2.4	-8.8	-2.3	11.5	-11.6
6	-2.5						4.1	-5.0	4.0		5.7	-2.4		14.0	-3.7
	-2.1				14.2		5.7	-3.4	3.1		5.9	-1.6	8.4	12.5	-3.2
	-2.4	-4.9	-18.8		-0.5		3.1	-0.7	1.7		8.1	-3.0	6.9	13.9	-1.0
	-1.3	-1.6	-11.2	7.1	1.1	1.7	-2.5	6.7	4.5		8.0	-3.0	4.3	14.5	-1.5
	-1.0	-0.4	-6.4	8.3	2.7	1.3	-2.6	1.1	5.7		7.0	-2.3	4.6	16.8	-2.5
	-0.7	1.6	-6.8	9.0	4.3	0.4	-3.0	3.5	7.0		5.9	-2.2	7.3	18.0	-3.0
	-1.2	3.4	-6.4	8.8	5.0	-1.2	-3.6	3.9	8.5		4.5	-1.6	7.4	18.1	-4.1
5	-6.2						-1.3	-11.1	-1.9	-5.7		-7.5		7.8	-6.6
	-8.8				7.4		-1.6	-9.1	-1.9	-5.9		-7.9	1.3	6.6	-7.3
	-10.8	-13.9	-26.9		-8.8		-6.6	-8.4	-5.7	-8.1		-11.6	-1.3	6.1	-7.2
	-8.9	-10.7	-19.1	-1.4	-7.4	-5.9	-10.6	-2.8	-2.8	-8.0		-10.0	-2.4	8.1	-7.9
	-7.2	-8.6	-12.8	2.9	-5.5	-6.8	-9.3	-6.5	-1.3	-7.0		-8.5	-1.3	11.1	-7.6
	-5.7	-4.8	-11.9	4.3	-2.3	-6.3	-8.8	-4.4	0.3	-5.9		-8.0	1.9	12.7	-8.3
	-4.7	-1.0	-8.9	5.4	0.7	-4.7	-6.3	-1.6	2.4	-4.5		-5.5	2.7	15.7	-7.8
4	0.6						7.8	-3.1	5.3	2.4	7.5			15.2	0.2
	-0.8				18.3		7.4	-2.0	4.7	1.6	7.9		10.9	15.0	0.6
	-0.2	-1.9	-12.9		3.4		6.7	2.1	5.2	3.0	11.6		10.5	17.2	2.6
	1.3	1.2	-6.7	10.8	3.7	4.9	0.8	8.8	5.3	3.0	10.0		6.7	18.8	1.4
	1.3	1.9	-2.8	11.5	5.1	4.0	0.3	3.6	8.0	2.3	8.5		6.4	19.8	0.5
	1.6	3.4	-2.2	11.3	6.6	3.0	0.5	5.5	10.0	2.2	8.0		10.0	21.2	-0.7
	1.0	5.7	-3.2	10.3	7.1	0.9	-0.6	5.6	8.8	1.6	5.5		8.6	21.3	-1.7
3	-9.0	-6.5	-13.8	4.1	-5.6	-4.0	-5.5	-7.6	-6.8	-6.9	1.3	-10.9		9.2	-7.6
	-6.1	-4.3	-8.8	1.8	-3.5	-7.6	-6.8	1.7	-1.4	-4.3	2.4	-10.5		12.8	-6.1
	-4.8	-6.6	-11.8	1.9	-3.9	-6.6	-7.0	-5.5	0.4	-4.6	1.3	-6.7		10.8	-6.6
	-7.9	-3.6	-12.0		-2.3		-9.8	-6.2	0.4	-7.3	-1.9	-6.4		11.7	-10.8
	-7.9						-8.5	-4.4	2.3	-7.4	-2.7	-10.0			-11.2
	-10.1	-11.9	-23.3	4.0	-9.0	-2.7	-3.5	-11.4	-6.3	-8.4	-1.3	-8.6		6.4	-9.1
2								-18.4	-6.5	-14.0	-7.8	-15.2			-17.2
					1.1		-5.5	-15.6	-13.0	-12.5	-6.6	-15.0			-16.0
	-18.1	-18.0	-31.1		-7.2		-13.1	-14.4	-11.2	-13.9	-6.1	-17.2	-6.4		-16.3
	-16.7	-17.3	-24.8	-9.6	-13.6	-14.8	-18.0	-8.4	-12.2	-14.5	-8.1	-18.8	-9.2		-17.5
	-18.6	-18.1	-22.0	-9.6	-13.5	-16.3	-19.9	-16.4	-11.5	-16.8	-11.1	-19.8	-12.8		-19.7
	-19.3	-16.9	-23.6	-9.3	-13.7	-18.9	-22.0	-16.0	-11.2	-18.0	-12.7	-21.2	-10.8		-21.9
	-20.5	-15.3	-23.8	-10.4	-13.7	-20.8	-22.8	-15.9	-11.5	-18.1	-15.7	-21.3	-11.7		-22.5
1	0.2						10.5	-1.7	5.5	3.7	6.6	-0.2		17.2	
	-1.2				17.2		7.2	-1.5	5.8	3.2	7.3	-0.6	9.1	16.0	
	-1.5	-0.2	-7.9		4.3		2.6	-0.1	2.0	1.0	7.2	-2.6	7.6	16.3	
	0.2	1.8	-3.6	9.2	3.1	4.0	-0.5	8.1	4.9	1.5	7.9	-1.4	6.1	17.5	
	0.7	4.4	-2.7	11.2	5.5	3.8	0.2	2.5	6.6	2.5	7.6	-0.5	6.6	19.7	
	2.1	7.3	-2.2	11.5	7.3	3.4	0.3	6.7	9.4	3.0	8.3	0.7	10.8	21.9	

	15**	14	13	12	11	10	9	8	7	6	5	4	3	2	1
	2.6	-4.1	-15.2	12.3	8.7	2.9	0.3	7.8	11.6	4.1	7.8	1.7	11.2	22.5	

* Rows correspond to periods in which given pair of countries is present in the data

** 15 The Middle East, 14 Africa, 13 India, 12 Vietnam, 11 The Philippines, 10 Korea, 9 China, 8 Russia, 7 Poland, 6 Germany 5 Italy, 4 England, 3 Cuba, 2 Mexico, 1 Canada

Table B.7: Occupational prestige distance by pair of countries over time: unskilled workers

	15**	14	13	12	11	10	9	8	7	6	5	4	3	2	1
15*							4.7	-2.9	2.7	1.7	5.9	0.2			-1.4
							6.3	-1.1	5.5	1.7	8.1	0.8	10.1		1.5
		-1.0	0.9	5.7	11.1		7.0	-1.4	-0.8	0.1	6.6	-3.6	5.7	11.1	-0.3
		2.4	1.5	5.9	6.1	4.5	5.3	6.5	1.1	-0.8	3.9	-2.0	4.8	9.2	-2.1
		3.1	1.0	4.8	5.2	0.0	3.8	1.8	3.7	0.9	3.8	-1.2	3.2	10.9	-0.8
		7.5	1.8	7.1	3.3	-2.5	3.1	1.4	5.2	0.9	4.2	-0.6	6.1	10.9	1.5
		4.8	-4.4		6.6	-0.8	6.6	5.4	8.0	1.6	3.7	-0.8	9.3	11.9	1.2
14	-2.4		-1.3	3.7	2.1	-2.0	3.7	1.8	0.7	-1.9	1.6	-3.7	4.3	9.5	-3.9
	-3.1		-2.9	2.1	-0.1	-4.5	1.4	-0.9	0.9	-4.1	0.6	-5.6	3.1	5.7	-3.8
	-7.5		-5.2	0.9	-1.4	-6.6	-1.2	-1.7	-0.4	-4.4	-4.1	-8.5	2.2	4.5	-9.0
	-4.8		-9.8		1.3		-7.4	-0.1	4.6	-3.4	1.0	-5.7	3.6	15.3	-7.3
	1.0		1.1	8.8	8.6	2.4	7.7	7.4	1.1	-0.4	6.9	-1.6	6.0	10.8	-0.6
13	-1.5	1.3		3.9	3.1	-0.8	1.4	0.5	1.2	-0.7	1.7	-2.4	1.8	9.2	-3.3
	-1.0	2.9		4.4	1.6	-1.5	2.6	0.5	4.1	-0.7	2.2	-4.9	3.7	8.7	-3.8
	-1.8	5.2		6.4	3.5	-2.3	4.0	3.3	4.5	0.6	0.3	-6.9	7.5	9.8	-2.7
	4.4	9.8			9.4		1.9	8.2	13.2	6.4	8.9	3.2	12.0	23.8	2.2
	-0.9	-1.1		4.6	5.1	2.3	5.0	5.7	1.1	-2.2	4.3	-2.4	4.0	8.8	-3.1
12	-5.9	-3.7	-3.9		0.4	-4.8	-1.7	-3.0	-4.2	-3.6	-3.1	-7.3	-0.7	5.3	-7.2
	-4.8	-2.1	-4.4		-1.1	-5.6	-1.1	-2.2	0.5	-5.4	-1.8	-8.6	0.2	4.0	-6.9
	-7.1	-0.9	-6.4		-1.2	-7.4	-1.0	-1.7	0.4	-6.0	-3.5	-8.8	0.8	4.0	-9.2
	-5.7	-8.8	-4.6		2.3	-1.8	-0.4	-0.9	-7.6	-6.4	-0.6	-8.3	-2.2	5.3	-7.7
11							-5.2	-18.3	-20.0	-13.8	-4.2	-16.9		-0.8	-16.1
	-11.1	-8.6	-5.1				-3.9	-11.7	-12.2	-8.9	-0.8	-13.2	-4.2	0.0	-11.2
	-6.1	-2.1	-3.1	-2.3		-3.3	-1.8	0.1	-4.6	-7.1	-0.8	-7.5	-1.7	3.6	-7.5
	-5.2	0.1	-1.6	-0.4		-3.9	-1.0	-1.8	-0.5	-3.7	0.3	-5.7	1.1	5.1	-6.9
	-3.3	1.4	-3.5	1.1		-3.9	-0.1	-0.7	3.3	-2.9	-3.6	-6.9	2.1	5.3	-6.5
	-6.6	-1.3	-9.4	1.2		-5.1	0.5	-0.3	0.3	-5.0	-1.2	-9.1	1.5	4.9	-8.4
10	0.0	2.0	0.8	4.8	3.9		2.5	2.4	3.0	0.3	2.3	-1.7	4.8	10.4	-2.8
	2.5	4.5	1.5	5.6	3.9		4.4	4.0	8.8	0.5	6.0	-2.1	6.6	10.5	-2.5
	0.8	6.6	2.3	7.4	5.1		5.6	6.0	7.6	2.5	3.7	-3.1	7.1	12.0	-3.7
	-4.5	-2.4	-2.3	1.8	3.3		2.1	3.4	-1.2	-4.4	1.0	-6.2	1.7	6.8	-6.0
9	-4.7							-7.7	-2.0	-2.4	1.0	-7.0			-7.8

	15^{**}	14	13	12	11	10	9	8	7	6	5	4	3	2	1
	-6.3				5.2			-7.5	-2.6	-5.8	1.1	-6.4	3.8	4.9	-6.8
	-7.0	-7.7	-5.0		3.9			-8.4	-7.9	-6.6	-0.7	-10.3	-1.3	5.0	-7.5
	-5.3	-3.7	-1.4	0.4	1.8	-2.1		0.1	-3.7	-5.7	-1.0	-7.7	-1.7	4.5	-6.6
	-3.8	-1.4	-2.6	1.7	1.0	-2.5		-2.1	-0.5	-1.6	-1.1	-7.3	-0.6	7.4	-5.2
	-3.1	1.2	-4.0	1.1	0.1	-4.4		-2.4	1.4	-4.1	-0.6	-7.3	1.3	5.8	-6.0
	-6.6	7.4	-1.9	1.0	-0.5	-5.6		-1.1	4.0	-4.6	-1.8	-10.2	1.1	5.9	-7.8
8	2.9						7.7		8.2	5.0	9.9	4.0		17.8	3.0
	1.1				18.3		7.5		6.4	3.7	8.8	2.0	11.3	16.5	2.3
	1.4	-7.4	-5.7		11.7		8.4		1.9	2.3	7.6	-2.3	6.8	9.7	0.9
	-6.5	-1.8	-0.5	0.9	-0.1	-3.4	-0.1		-4.0	-7.0	-1.1	-7.6	-1.8	3.3	-7.9
	-1.8	0.9	-0.5	3.0	1.8	-2.4	2.1		0.6	-2.3	0.8	-4.9	2.9	8.9	-3.4
	-1.4	1.7	-3.3	2.2	0.7	-4.0	2.4		4.0	-2.8	2.0	-5.0	4.4	6.2	-4.5
	-5.4	0.1	-8.2	1.7	0.3	-6.0	1.1		1.9	-3.7	-1.2	-6.9	3.3	5.2	-5.4
7	-2.7						2.0	-8.2		-3.5	1.1	-4.2		6.8	-4.6
	-5.5				20.0		2.6	-6.4		-3.2	1.7	-4.6	6.3	12.8	-4.1
	0.8	-1.1	-1.1		12.2		7.9	-1.9		-0.6	3.5	-4.1	6.2	8.0	-2.6
	-1.1	-0.7	-1.2	7.6	4.6	1.2	3.7	4.0		-3.6	1.3	-3.3	2.1	7.7	-4.4
	-3.7	-0.9	-4.1	4.2	0.5	-3.0	0.5	-0.6		-3.2	0.1	-3.8	1.2	7.3	-4.7
	-5.2	0.4	-4.5	-0.5	-3.3	-8.8	-1.4	-4.0		-5.7	-2.0	-8.1	-0.9	5.0	-5.5
	-8.0	-4.6	-13.2	-0.4	-0.3	-7.6	-4.0	-1.9		-6.1	-4.7	-11.8	1.2	5.5	-9.2
6	-1.7						2.4	-5.0	3.5		4.4	-2.6		13.1	-3.0
	-1.7				13.8		5.8	-3.7	3.2		5.6	-1.3	8.3	12.4	-2.1
	-0.1	0.4	2.2		8.9		6.6	-2.3	0.6		4.8	-3.8	5.7	8.5	-1.8
	0.8	1.9	0.7	6.4	7.1	4.4	5.7	7.0	3.6		4.9	-1.6	6.0	10.6	-1.1
	-0.9	4.1	0.7	3.6	3.7	-0.3	1.6	2.3	3.2		2.9	-1.7	4.7	9.3	-2.6
	-0.9	4.4	-0.6	5.4	2.9	-0.5	4.1	2.8	5.7		3.2	-1.3	5.4	9.4	-1.3
	-1.6	3.4	-6.4	6.0	5.0	-2.5	4.6	3.7	6.1		1.0	-2.7	6.8	8.8	-2.9
5	-5.9						-1.0	-9.9	-1.1	-4.4		-6.4		7.8	-5.3
	-8.1				7.3		-1.1	-8.8	-1.7	-5.6		-7.4	1.5	6.8	-6.0
	-6.6	-6.9	-4.3		4.2		0.7	-7.6	-3.5	-4.8		-8.6	0.1	4.2	-5.5
	-3.9	-1.6	-1.7	0.6	0.8	-1.0	1.0	1.1	-1.3	-4.9		-6.4	-0.4	4.7	-5.4
	-3.8	-0.6	-2.2	3.1	0.8	-2.3	1.1	-0.8	-0.1	-2.9		-4.7	0.6	8.3	-3.8
	-4.2	4.1	-0.3	1.8	-0.3	-6.0	0.6	-2.0	2.0	-3.2		-6.5	1.1	6.5	-3.0
	-3.7	-1.0	-8.9	3.5	3.6	-3.7	1.8	1.2	4.7	-1.0		-5.7	6.1	9.6	-2.6
4	-0.2						7.0	-4.0	4.2	2.6	6.4			14.0	0.5
	-0.8				16.9		6.4	-2.0	4.6	1.3	7.4		10.2	14.1	0.7
	3.6	1.6	2.4		13.2		10.3	2.3	4.1	3.8	8.6		10.3	14.1	2.0
	2.0	3.7	2.4	8.3	7.5	6.2	7.7	7.6	3.3	1.6	6.4		6.3	11.7	0.0
	1.2	5.6	4.9	7.3	5.7	1.7	7.3	4.9	3.8	1.7	4.7		7.4	13.2	-0.8
	0.6	8.5	6.9	8.6	6.9	2.1	7.3	5.0	8.1	1.3	6.5		9.3	12.3	0.8
	0.8	5.7	-3.2	8.8	9.1	3.1	10.2	6.9	11.8	2.7	5.7		10.2	14.4	1.1
3	-5.7	-4.3	-1.8	0.7	1.7	-4.8	1.3	-6.8	-6.2	-5.7	-0.1	-10.3		5.5	-7.6
	-4.8	-3.1	-3.7	-0.2	-1.1	-6.6	1.7	1.8	-2.1	-6.0	0.4	-6.3		6.3	-6.4
	-3.2	-2.2	-7.5	-0.8	-2.1	-7.1	0.6	-2.9	-1.2	-4.7	-0.6	-7.4		4.4	-6.0
	-6.1	-3.6	-12.0		-1.5		-1.3	-4.4	0.9	-5.4	-1.1	-9.3		3.9	-6.7

	15**	14	13	12	11	10	9	8	7	6	5	4	3	2	1
	-9.3						-1.1	-3.3	-1.2	-6.8	-6.1	-10.2			-9.0
	-10.1	-6.0	-4.0	2.2	4.2	-1.7	-3.8	-11.3	-6.3	-8.3	-1.5	-10.2		2.8	-8.5
2								-17.8	-6.8	-13.1	-7.8	-14.0			-15.6
					0.8		-4.9	-16.5	-12.8	-12.4	-6.8	-14.1			-15.4
	-11.1	-10.8	-8.8		0.0		-5.0	-9.7	-8.0	-8.5	-4.2	-14.1	-2.8		-12.4
	-9.2	-9.5	-9.2	-5.3	-3.6	-6.8	-4.5	-3.3	-7.7	-10.6	-4.7	-11.7	-5.5		-11.9
	-10.9	-5.7	-8.7	-5.3	-5.1	-10.4	-7.4	-8.9	-7.3	-9.3	-8.3	-13.2	-6.3		-12.3
	-10.9	-4.5	-9.8	-4.0	-5.3	-10.5	-5.8	-6.2	-5.0	-9.4	-6.5	-12.3	-4.4		-10.5
	-11.9	-15.3	-23.8	-4.0	-4.9	-12.0	-5.9	-5.2	-5.5	-8.8	-9.6	-14.4	-3.9		-13.1
1	1.4						7.8	-3.0	4.6	3.0	5.3	-0.5		15.6	
	-1.5				16.1		6.8	-2.3	4.1	2.1	6.0	-0.7	8.5	15.4	
	0.3	3.9	3.3		11.2		7.5	-0.9	2.6	1.8	5.5	-2.0	7.6	12.4	
	2.1	3.8	3.8	7.2	7.5	6.0	6.6	7.9	4.4	1.1	5.4	0.0	6.4	11.9	
	0.8	9.0	2.7	6.9	6.9	2.8	5.2	3.4	4.7	2.6	3.8	0.8	6.0	12.3	
	-1.5	7.3	-2.2	9.2	6.5	2.5	6.0	4.5	5.5	1.3	3.0	-0.8	6.7	10.5	
	-1.2	0.6	3.1	7.7	8.4	3.7	7.8	5.4	9.2	2.9	2.6	-1.1	9.0	13.1	

* Rows correspond to periods in which given pair of countries is present in the data

** 15 The Middle East, 14 Africa, 13 India, 12 Vietnam, 11 The Philippines, 10 Korea, 9 China, 8 Russia, 7 Poland, 6 Germany 5 Italy, 4 England, 3 Cuba, 2 Mexico, 1 Canada

Table B.8: Percentage of times that immigrants from a given country share popular occupations across metropolitan areas in given year 1940-2011

	All individuals							Unskilled individuals						
	1940	1950	1970	1980	1990	2000	2011	1940	1950	1970	1980	1990	2000	2011
Canada	0.63	0.60	0.45	0.44	0.32	0.51	0.52	0.43	0.50	0.30	0.46	0.32	0.25	0.25
Mexico	0.50	0.67	0.88	0.64	0.75	0.73	0.84	0.33	0.50	0.80	0.31	0.76	0.67	0.83
Cuba		1.00	0.57	0.39	0.52	0.48	0.54		1.00	0.50	0.35	0.65	0.57	0.43
England	0.56	0.50	0.40	0.20	0.23	0.33	0.33	0.33	0.44	0.33	0.25	0.08	0.14	0.25
Italy	0.31	0.40	0.65	0.57	0.59	0.50	0.35	0.27	0.28	0.55	0.59	0.52	0.40	0.60
Germany	0.55	0.44	0.50	0.39	0.46	0.40	0.32	0.25	0.33	0.50	0.30	0.37	0.25	0.47
Poland	0.38	0.42	0.15	0.50	0.53	0.65	0.47	0.28	0.31	0.19	0.53	0.36	0.50	0.42
Other USSR/Russia	0.50	0.63	0.30	0.45	0.42	0.43	0.50	0.46	0.45	0.44	0.36	0.33	0.44	0.43
China	1.00	0.50	0.60	0.50	0.47	0.43	0.38	1.00	0.50	0.75	0.50	0.67	0.70	0.63
Korea				0.55	0.72	0.48	0.54				0.40	0.56	0.50	0.47
Philippines		0.50	0.71	0.38	0.59	0.46	0.61	1.00	0.67	0.50	0.36	0.67	0.38	0.56
Vietnam				0.40	0.67	0.48	0.53				0.30	0.58	0.53	0.49
India			0.50	0.70	0.50	0.57	0.57				0.33	0.47	0.79	0.67
Africa			0.50	0.41	0.42	0.39	0.46			1.00	1.00	1.00	0.81	0.71
Middle East	0.50	0.00	0.67	0.33	0.46	0.54	0.55	1.00	0.00	0.50	0.71	0.55	0.69	0.59

Table B.9: Percentage of times that country A is ranked above country B

All	Af	Ind	Viet	Phil	Kor	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
ME	0.63	0.09	1.00	0.81	0.55	0.34	0.64	0.90	0.59	0.93	0.32	0.97	1.00	0.31
Africa		0.05	0.92	0.66	0.33	0.21	0.56	0.91	0.36	0.81	0.26	0.84	1.00	0.25
India			0.99	0.97	0.91	0.71	0.94	0.94	0.94	0.99	0.80	0.99	1.00	0.74
Vietnam				0.19	0.00	0.03	0.19	0.28	0.00	0.22	0.00	0.29	0.98	0.00
Philippines					0.14	0.11	0.48	0.79	0.18	0.67	0.08	0.82	0.97	0.08
Korea						0.22	0.83	0.86	0.46	0.90	0.22	0.86	1.00	0.17
China							0.74	0.85	0.76	0.90	0.54	0.93	1.00	0.49
Russia								0.78	0.37	0.84	0.24	0.92	1.00	0.18
Poland									0.13	0.63	0.10	0.51	1.00	0.09
Germany										0.92	0.18	0.93	1.00	0.15
Italy											0.01	0.46	1.00	0.02
England												0.96	1.00	0.44
Cuba													1.00	0.02
Mexico														0.00
Unskilled	Af	Ind	Viet	Phil	Kor	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
ME	0.95	0.68	1.00	1.00	0.57	0.92	0.62	0.81	0.59	0.95	0.33	0.95	1.00	0.45
Africa		0.16	0.74	0.41	0.10	0.68	0.44	0.58	0.14	0.44	0.11	0.88	0.98	0.15
India			0.95	0.89	0.30	0.85	0.71	0.92	0.39	0.82	0.00	0.85	1.00	0.16
Vietnam				0.37	0.00	0.40	0.20	0.33	0.03	0.00	0.00	0.43	1.00	0.00
Philippines					0.08	0.50	0.39	0.58	0.03	0.28	0.00	0.57	0.95	0.00
Korea						0.87	0.94	0.86	0.46	0.84	0.00	0.92	1.00	0.07
China							0.31	0.29	0.08	0.30	0.00	0.59	1.00	0.03
Russia								0.71	0.50	0.76	0.42	0.80	1.00	0.50
Pol									0.10	0.53	0.04	0.71	1.00	0.11
Germany										0.93	0.18	1.00	1.00	0.19
Italy											0.00	0.64	1.00	0.05
England												1.00	1.00	0.56
Cuba													0.98	0.00
Mexico														0.00
All Unskilled	Af	Ind	Viet	Phil	Kor	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
ME	-0.32	-0.58	0.00	-0.19	-0.01	-0.59	0.02	0.09	0.00	-0.01	-0.01	0.02	0.00	-0.14
Africa		-0.10	0.17	0.25	0.23	-0.47	0.12	0.33	0.23	0.37	0.15	-0.04	0.02	0.10
India			0.04	0.08	0.61	-0.14	0.22	0.02	0.55	0.17	0.80	0.14	0.00	0.58
Vietnam				-0.18	0.00	-0.37	-0.01	-0.06	-0.03	0.22	0.00	-0.14	-0.02	0.00
Philippines					0.06	-0.39	0.09	0.21	0.15	0.39	0.08	0.25	0.01	0.08
Korea						-0.65	-0.12	0.01	-0.01	0.05	0.22	-0.05	0.00	0.10
China							0.43	0.56	0.68	0.60	0.54	0.34	0.00	0.45
Russia								0.07	-0.13	0.07	-0.18	0.12	0.00	-0.32
Poland									0.03	0.10	0.06	-0.20	0.00	-0.03
Germany										-0.01	0.00	-0.07	0.00	-0.04
Italy											0.01	-0.18	0.00	-0.04
England												-0.04	0.00	-0.12
Cuba													0.02	0.02
Mexico														0.00

Figure B.2: Distribution of cut off points in the middle and top sectors

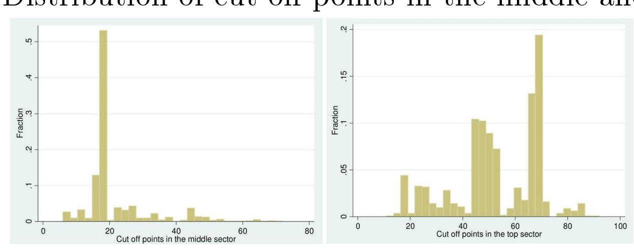

Table B.10: Shares of workers in top, middle and bottom sector by year and origin

	All workers							Unskilled workers						
	1940	1950	1970	1980	1990	2000	2011	1940	1950	1970	1980	1990	2000	2011
Top sector														
Canada	0.42	0.43	0.53	0.63	0.76	0.82	0.84	0.33	0.42	0.65	0.80	0.85	1.00	1.00
Mexico	0.00	0.06	0.03	0.13	0.09	0.10	0.09	0.00	0.06	0.04	0.21	0.20	0.25	0.27
Cuba			0.16	0.45	0.50	0.57	0.45			0.10	0.33	0.54	0.38	0.49
England	0.60	0.79	0.80	0.74	0.81	0.89	0.87	0.50	0.82	0.81	0.97	1.00	1.00	1.00
Italy	0.08	0.18	0.09	0.19	0.36	0.47	0.62	0.14	0.17	0.11	0.31	0.43	0.49	0.77
Germany	0.22	0.40	0.43	0.45	0.59	0.73	0.66	0.23	0.34	0.52	0.77	0.85	0.95	1.00
Poland	0.10	0.19	0.24	0.34	0.27	0.36	0.29	0.07	0.17	0.42	0.42	0.45	0.63	0.51
Russia	0.69	0.56	0.49	0.32	0.68	0.65	0.58	0.68	0.55	0.62	0.33	0.58	0.78	0.62
China	0.00	0.18	0.41	0.74	0.74	0.84	0.84	0.00	0.18	0.19	0.22	0.29	0.27	0.45
Korea				0.51	0.67	0.75	0.72				0.50	0.79	0.84	0.86
Philippines		0.00	0.42	0.48	0.47	0.50	0.43		0.00	0.00	0.32	0.59	0.63	0.59
Vietnam				0.41	0.25	0.29	0.29				0.74	0.45	0.45	0.45
India			1.00	0.89	0.79	0.86	0.80				0.85	0.75	0.80	0.82
Africa			1.00	0.78	0.71	0.71	0.49				0.83	0.63	0.70	0.57
Middle East	0.41	0.50	0.73	0.72	0.75	0.80	0.79	0.37	0.49	0.49	0.55	0.76	0.78	0.90
Middle sector														
Canada	0.51	0.52	0.26	0.30	0.22	0.16	0.15	0.58	0.54	0.29	0.16	0.13	0.00	0.00
Mexico	0.19	0.36	0.20	0.37	0.32	0.33	0.32	0.18	0.41	0.32	0.40	0.42	0.38	0.34
Cuba			0.31	0.41	0.31	0.30	0.38			0.78	0.43	0.30	0.50	0.37
England	0.32	0.17	0.18	0.25	0.18	0.11	0.13	0.46	0.15	0.20	0.00	0.00	0.00	0.00
Italy	0.35	0.41	0.38	0.52	0.27	0.30	0.19	0.32	0.43	0.61	0.43	0.41	0.43	0.18
Germany	0.73	0.56	0.39	0.44	0.37	0.24	0.30	0.71	0.62	0.44	0.21	0.15	0.05	0.00
Poland	0.64	0.64	0.25	0.55	0.39	0.42	0.50	0.67	0.65	0.53	0.54	0.41	0.26	0.37
Russia	0.24	0.27	0.30	0.60	0.27	0.22	0.26	0.24	0.33	0.33	0.33	0.29	0.17	0.20
China	0.00	0.00	0.08	0.10	0.13	0.08	0.10	0.00	0.00	0.00	0.15	0.58	0.69	0.51
Korea				0.31	0.21	0.18	0.21				0.41	0.17	0.13	0.12
Philippines		0.00	0.25	0.36	0.42	0.40	0.44		0.00	0.50	0.50	0.29	0.23	0.25
Vietnam				0.53	0.50	0.52	0.46				0.26	0.52	0.48	0.50
India			0.00	0.09	0.17	0.11	0.18				0.15	0.22	0.16	0.15
Africa			0.00	0.16	0.22	0.18	0.31				0.17	0.21	0.19	0.11
Middle East	0.36	0.30	0.14	0.18	0.18	0.14	0.17	0.37	0.31	0.51	0.28	0.22	0.18	0.09
Bottom sector														
Canada	0.07	0.05	0.21	0.06	0.03	0.02	0.02	0.09	0.04	0.06	0.04	0.02	0.00	0.00
Mexico	0.81	0.59	0.77	0.50	0.59	0.56	0.59	0.82	0.53	0.64	0.39	0.38	0.38	0.39
Cuba			0.53	0.14	0.18	0.13	0.18			0.12	0.25	0.16	0.12	0.15
England	0.07	0.04	0.02	0.01	0.01	0.00	0.00	0.04	0.03	0.00	0.03	0.00	0.00	0.00
Italy	0.57	0.41	0.52	0.29	0.37	0.23	0.18	0.54	0.39	0.28	0.27	0.17	0.08	0.05
Germany	0.06	0.05	0.18	0.11	0.05	0.03	0.04	0.06	0.05	0.05	0.02	0.00	0.00	0.00
Poland	0.27	0.17	0.51	0.10	0.34	0.22	0.20	0.26	0.18	0.05	0.04	0.14	0.11	0.12
Russia	0.07	0.17	0.21	0.08	0.05	0.13	0.16	0.08	0.12	0.05	0.33	0.13	0.06	0.18
China	1.00	0.82	0.51	0.16	0.13	0.07	0.05	1.00	0.82	0.81	0.63	0.13	0.04	0.04
Korea				0.18	0.12	0.07	0.07				0.09	0.05	0.03	0.01
Philippines		1.00	0.33	0.16	0.11	0.11	0.13		1.00	0.50	0.18	0.11	0.14	0.16
Vietnam				0.06	0.25	0.19	0.25				0.00	0.03	0.06	0.05
India			0.00	0.01	0.04	0.03	0.02				0.00	0.03	0.04	0.03
Africa			0.00	0.06	0.07	0.10	0.20				0.00	0.16	0.12	0.32
Middle East	0.23	0.20	0.13	0.09	0.07	0.05	0.04	0.26	0.20	0.00	0.17	0.03	0.04	0.02

Table B.11: Shares in the top sector in selected regions 1940-2011

	1940	1950	1970	1980	1990	2000	2011
Canada							
Boston, MA	0.25	0.26	0.28	0.48	0.58	1	
Buffalo-Niagara Falls, NY	0	0	1	0.53			
Chicago-Gary-Lake, IL	0.58	1	1	1			
Detroit, MI	0.42	0.42	0.48	0.42	0.43	1	
Los Angeles-Long Beach, CA	0.53	0.67	0.49	0.64	0.69	1	1
New York-Northeastern NJ	0.41	0.47	1	1	1	1	1
Providence-Fall River-Pawtucket, MA/RI	0	0					
Springfield-Holyoke-Chicopee, MA	0	0					

	1940	1950	1970	1980	1990	2000	2011
England							
Boston, MA	0	1					
Chicago-Gary-Lake, IL	1			1			
Detroit, MI	0.51	0.45		1			
Los Angeles-Long Beach, CA	0.47	1	0.61	0.79	1	1	1
New York-Northeastern NJ	0.37	0.46	1	1	1	1	1
Philadelphia, PA/NJ	0						
San Francisco-Oakland-Vallejo, CA	1			1			
Germany							
Buffalo-Niagara Falls, NY	0	0					
Chicago-Gary-Lake, IL	0.28	0.34	0.32	0.58	0.73	1	1
Cleveland, OH	0						
Detroit, MI	0.45	0.46	1	0.51			
Los Angeles-Long Beach, CA	1	1	0.34	0.7	1	1	
New York-Northeastern NJ	0.29	0.39	0.47	0.62	0.66	1	1
Philadelphia, PA/NJ	0	0.42	0.39	0.49	0.55	1	1
Pittsburgh-Beaver Valley, PA	0						
San Francisco-Oakland-Vallejo, CA	0	0		0.59			
Italy							
Boston, MA	0.18	0.22	0.18	0.37	0.47	0.59	0.6
Buffalo-Niagara Falls, NY	0	0	0	0			
Chicago-Gary-Lake, IL	0.23	0.26	0.17	0.41	0.44	0.55	1
Cleveland, OH	0	0		0.24			
Detroit, MI	0	0.24	0.28	0.24	0	0.44	
Hartford-Bristol-Middleton-New Britain,	0		0	0			
Los Angeles-Long Beach, CA	0	0.41	0	0.49	1		
New York-Northeastern NJ	0.19	0.23	0.2	0.3	0.39	0.42	0.49
Philadelphia, PA/NJ	0.19	0.19	0.19	0.29	0.34	0.52	1
Pittsburgh-Beaver Valley, PA	0.15	0.2					
Providence-Fall River-Pawtucket, MA/RI	0.31	0					
San Francisco-Oakland-Vallejo, CA	0.2	0.25	0	0.47			
Poland							
Boston, MA	0	0					
Buffalo-Niagara Falls, NY	0	0		0			
Chicago-Gary-Lake, IL	0.16	0.21	0.22	0.42	0.42	0.46	0.44
Cleveland, OH	0	0		0			
Detroit, MI	0.24	0.23	0.42	0.4	0		
Hartford-Bristol-Middleton-New Britain,	0		0	0			
New York-Northeastern NJ	0.28	0.37	0.44	0.49	0.47	0.32	0.42
Philadelphia, PA/NJ	0	0		0.44			
Pittsburgh-Beaver Valley, PA	0	0					
Springfield-Holyoke-Chicopee, MA	0	0					
Russia							
Boston, MA	0.52	0.44					
Chicago-Gary-Lake, IL	0.47	0.51	0.45	0		1	0.54
Detroit, MI	1	0.58					
Los Angeles-Long Beach, CA	1	0.69	1	1	0.6	0.58	0.57

	1940	1950	1970	1980	1990	2000	2011
New York-Northeastern NJ	0.46	0.5	0.51	0	0.45	0.47	0.48
Philadelphia, PA/NJ	0.59	0.56	0.52				
Mexico							
Chicago-Gary-Lake, IL			0	0	0.12	0.21	0.24
Houston-Brazoria, TX						0.3	0.31
Los Angeles-Long Beach, CA			0	0.16	0.11	0.28	0.29
Anaheim-Santa Ana-Garden Grove, CA					0	0.21	0.46
New York-Northeastern NJ						0.23	0.13
Phoenix, AZ						0.21	0.36
Riverside-San Bernardino,CA						0.24	0.29
San Diego, CA					0	0.31	0.31
San Francisco-Oakland-Vallejo, CA				0	0	0.2	0.2
San Jose, CA						0.21	0.24
Cuba							
Chicago-Gary-Lake, IL			0	0.42	1		
Los Angeles-Long Beach, CA			0	0.5	0.51	0.59	1
New York-Northeastern, NJ			0.28	0.4	0.35	0.39	
Jersey City, NJ			0.23	0.37	0.4	0.41	0.55
Newark, NJ			0	0.3	0.32		
China							
Boston, MA						0	0.26
Chicago-Gary-Lake, IL						0	0
Honolulu, HI						0.5	0.47
Los Angeles-Long Beach, CA					0	0.46	0.47
New York-Northeastern NJ			0	0.36	0.19	0.24	0.29
San Francisco-Oakland-Vallejo, CA			0	0	0.37	0.31	0.35
Washington, DC/MD/VA						0	0
India							
Chicago-Gary-Lake, IL				1	0.65	0.53	0.6
Houston-Brazoria, TX					1	1	1
Los Angeles-Long Beach, CA					1	0.77	0.66
Anaheim-Santa Ana-Garden Grove, CA					1		
New York-Northeastern NJ				0.55	0.39	0.39	0.38
Nassau Co, NY					1	1	0.69
Jersey City, NJ					1	1	1
Washington, DC/MD/VA					0.68	0.49	0.51
Korea							
Los Angeles-Long Beach, CA				0.49	0.6	0.61	0.65
New York-Northeastern NJ				1	0.56	0.5	0.65
Washington, DC/MD/VA				0	0.61	0.66	0.6
Philippines							
Los Angeles-Long Beach, CA		0	0	0.37	0.51	0.52	0.53
San Diego, CA			0	0.22	0.34	0.4	0.44
San Francisco-Oakland-Vallejo, CA		0	0	0.36	0.43	0.42	0.49

	1940	1950	1970	1980	1990	2000	2011
Vietnam							
Boston, MA					0	0.47	0.52
Houston-Brazoria, TX				1	0.59	0.48	0.53
Los Angeles-Long Beach, CA				0.5	0.49	0.44	0.48
Oakland, CA					0.41	0.4	0.38
Washington, DC/MD/VA					0.5	0.44	0.39
Africa							
Atlanta, GA						0.62	0.5
Minneapolis-St. Paul, MN						1	0.59
New York-Northeastern NJ				0.65	0.45	0.41	0.37
Newark, NJ						0	0.49
Middle East							
Chicago-Gary-Lake, IL						0.68	0.64
Detroit, MI						0.36	0.49
Los Angeles-Long Beach, CA						0.64	0.69
New York-Northeastern, NJ			0.37	0.49	0.48	0.52	0.55

Table B.12: Percentage of times that country A (row) has a larger network than country B (column) in the top and middle sector

Top sector

	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Midle East	0.66	0.62	0.98	0.84	0.54	0.73	0.60	0.82	0.77	0.89	0.60	0.69	1.00	0.67
Africa		0.56	0.98	0.83	0.51	0.57	0.51	0.87	0.73	0.80	0.58	0.76	1.00	0.59
India			1.00	0.87	0.68	0.66	0.45	0.87	0.85	0.93	0.56	0.80	1.00	0.68
Vietnam				0.49	0.10	0.10	0.13	0.63	0.11	0.14	0.08	0.39	0.95	0.08
Philippines					0.13	0.19	0.18	0.84	0.33	0.75	0.16	0.51	0.95	0.16
Korea						0.59	0.69	0.87	0.68	0.89	0.44	0.72	1.00	0.47
China							0.47	0.81	0.73	0.92	0.47	0.75	0.99	0.65
Russia								0.75	0.54	0.78	0.43	0.76	0.94	0.38
Poland									0.25	0.59	0.17	0.40	1.00	0.38
Germany										0.85	0.25	0.63	1.00	0.38
Italy											0.13	0.33	1.00	0.26
England												0.92	1.00	0.81
Cuba													0.98	0.35
Mexico														0.00

Middle sector

	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East	0.69	0.74	0.16	0.18	0.68	0.75	0.60	0.29	0.37	0.31	0.75	0.44	0.30	0.57
Africa		0.72	0.09	0.13	0.54	0.71	0.51	0.26	0.39	0.30	0.72	0.35	0.24	0.58
India			0.18	0.14	0.52	0.74	0.51	0.23	0.30	0.32	0.65	0.36	0.24	0.55
Vietnam				0.43	0.80	0.97	0.75	0.50	0.81	0.71	0.92	0.70	0.60	0.92
Philippines					0.92	0.98	0.85	0.40	0.67	0.45	0.90	0.66	0.60	0.90
Korea						0.74	0.46	0.22	0.32	0.15	0.67	0.41	0.38	0.68
China							0.50	0.30	0.29	0.24	0.71	0.38	0.22	0.55
Russia								0.43	0.56	0.39	0.80	0.47	0.51	0.79
Poland									0.70	0.72	0.73	0.75	0.62	0.68
Germany										0.44	0.80	0.52	0.38	0.80
Italy											0.76	0.56	0.50	0.62
England												0.43	0.16	0.58
Cuba													0.50	0.71
Mexico														0.78

Table B.13: Percentage of times that country A (row) has a larger network than country B (column) in the top and middle sector: unskilled workers

Top sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Midle East		0.29	0.60	0.90	0.83	0.25	1.00	0.83	0.91	0.33	0.88	0.00	1.00	1.00	0.40
Africa	0.71		0.33	0.71	0.75	0.33	0.89	0.50	0.75	0.25	0.60	0.00	0.80	1.00	0.25
India	0.30	0.33		0.93	0.71	0.33	1.00	0.50	0.60	0.00	0.56	0.00	0.75	1.00	0.33
Vietnam	0.00	0.29	0.07		0.33	0.00	0.61	0.17	0.50	0.00	0.20	0.00	0.25	0.87	0.00
Philippines	0.17	0.25	0.14	0.61		0.17	0.72	0.00	0.50	0.00	0.25	0.00	0.33	0.93	0.00
Korea	0.33	0.44	0.42	1.00	0.50		1.00	0.67	1.00	0.09	0.89	0.00	0.75	1.00	0.00
China	0.00	0.11	0.00	0.39	0.28	0.00		0.00	0.00	0.00	0.00	0.00	0.33	0.87	0.00
Russia	0.17	0.33	0.33	0.83	0.75	0.33	1.00		0.50	0.00	0.60	0.00	0.40	0.89	0.25
Poland	0.00	0.25	0.40	0.50	0.50	0.00	1.00	0.50		0.10	0.69	0.00	0.71	0.91	0.25
Germany	0.42	0.38	0.44	0.89	0.71	0.45	1.00	0.80	0.90		0.93	0.00	0.89	1.00	0.27
Italy	0.06	0.20	0.22	0.80	0.75	0.11	1.00	0.20	0.31	0.00		0.00	0.70	0.94	0.20
England	0.67	0.00	0.33	1.00	1.00	1.00	1.00	0.67	0.67	0.60	0.75		1.00	1.00	0.50
Cuba	0.00	0.20	0.25	0.50	0.67	0.25	0.67	0.60	0.29	0.11	0.30	0.00		0.94	0.00
Mexico	0.00	0.00	0.00	0.13	0.07	0.00	0.13	0.11	0.00	0.00	0.00	0.00	0.06		0.00
Canada	0.40	0.00	0.33	0.86	0.75	0.75	1.00	0.75	0.75	0.27	0.80	0.00	0.71	1.00	

Middle sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Midle East		0.86	0.40	0.00	0.17	0.25	0.27	0.67	0.18	0.38	0.13	0.75	0.00	0.00	0.50
Africa	0.14		0.11	0.00	0.25	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00
India	0.50	0.33		0.00	0.14	0.17	0.00	0.33	0.00	0.17	0.22	0.00	0.00	0.00	0.33
Vietnam	0.90	1.00	1.00		0.78	1.00	0.17	1.00	1.00	1.00	1.00	1.00	0.50	0.66	0.86
Philippines	0.83	0.75	0.57	0.17		0.17	0.17	0.75	0.50	0.40	0.50	1.00	0.67	0.31	1.00
Korea	0.33	0.78	0.50	0.00	0.50		0.00	0.83	0.14	0.50	0.25	1.00	0.25	0.12	1.00
China	0.64	1.00	0.93	0.83	0.78	0.91		0.86	0.43	0.56	0.46	1.00	0.33	0.83	0.63
Russia	0.33	0.83	0.50	0.00	0.00	0.17	0.14		0.25	0.50	0.20	0.50	0.20	0.11	0.75
Poland	0.73	1.00	1.00	0.00	0.50	0.86	0.43	0.75		0.67	0.53	1.00	0.43	0.09	0.75
Germany	0.50	0.33	0.17	0.00	0.20	0.13	0.33	0.25	0.33		0.29	0.67	0.33	0.08	0.67
Italy	0.69	0.80	0.56	0.00	0.50	0.63	0.46	0.60	0.41	0.64		0.67	0.30	0.29	0.70
England	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
Cuba	1.00	1.00	1.00	0.25	0.33	0.75	0.67	0.80	0.57	0.67	0.70	1.00		0.44	0.57
Mexico	1.00	1.00	1.00	0.34	0.69	0.82	0.17	0.89	0.91	0.85	0.71	1.00	0.56		1.00
Canada	0.3	1	0.25	0	0.00	0.00	0.38	0.25	0.25	0.17	0.30	0.50	0.14	0.00	

* Since there were many ties in the data the averages below the diagonal do not equal one minus the averages above the diagonal as it was the case in Table B.9 and in Table B.12

Table B.14: Individual characteristic by sector by group

	Individuals in the top sector							All other individuals						
	Age	Edu	Eng*	Arr	Stay	Net2**	Net1**	Age	Edu	Eng	Arr	Stay	Net2	Net1
Canada	43.79	14.37	0.88	2.34	34.35	0.7	0.24	42.86	11.71	0.73	1.97	30.68	0.57	0.32
Mexico	37.36	11.55	0.75	2.24	43.96	0.17	0.4	34.9	9.47	0.46	2.44	41.2	0.14	0.39
Cuba	44.29	13.66	0.84	3.02	24.93	0.39	0.34	44.35	11.33	0.56	2.99	25.76	0.36	0.35
England	43.36	14.37	0.88	2.41	32.84	0.78	0.2	42.09	12.21	0.79	2.2	30.03	0.71	0.25
Italy	46.1	11.8	0.68	1.52	33.42	0.32	0.33	47	8.92	0.48	1.42	27.32	0.25	0.35
Germany	43.53	14.26	0.87	2.49	31.43	0.6	0.32	40.93	11.88	0.77	2.3	28.04	0.5	0.38
Poland	46.09	12.52	0.66	1.32	38.29	0.33	0.41	46.15	10.3	0.48	1.34	36.63	0.27	0.44
Russia	43.23	13.51	0.67	1.72	38.63	0.55	0.28	43.89	11.74	0.54	1.92	37.57	0.48	0.31
China	41.52	15.7	0.91	3.2	32.33	0.65	0.18	42.89	11.98	0.53	2.57	38.44	0.53	0.22
Korea	41.82	15.15	0.8	3.86	21.93	0.65	0.23	41.32	13.48	0.64	3.9	20.38	0.59	0.26
Philippines	42.09	14.94	0.98	2.91	33.1	0.45	0.37	41.29	13.26	0.92	2.98	31.78	0.36	0.41
Vietnam	38.88	14.55	0.9	4.45	17.36	0.38	0.42	40.31	11.86	0.64	4.45	17.64	0.33	0.44
India	39.75	16.06	0.98	4.1	21.58	0.72	0.21	39.49	13.9	0.9	3.93	23.64	0.61	0.28
Africa	42	15.55	0.99	4.04	21.19	0.55	0.26	39.27	13.55	0.94	4.06	22.86	0.45	0.31
Middle East	41.09	14.66	0.96	2.78	35.25	0.66	0.23	39.13	12.26	0.87	2.58	36.72	0.59	0.26

	Individuals in the middle sector							Individuals in the bottom sector						
	Age	Edu	Eng	Arr	Stay	Net2	Net1	Age	Edu	Eng	Arr	Stay	Net2	Net1
Canada	43.09	12.05	0.76	2.04	30.69	0.58	0.32	42.39	10.99	0.69	1.82	30.66	0.55	0.31
Mexico	35.29	9.72	0.51	2.31	42.41	0.15	0.41	34.56	9.26	0.42	2.54	40.15	0.14	0.37
Cuba	43.75	11.72	0.62	3.01	25.57	0.36	0.36	45.08	10.86	0.47	2.97	25.99	0.35	0.35
England	42.51	12.54	0.81	2.26	30.62	0.72	0.25	41.2	11.52	0.74	2.09	28.77	0.71	0.24
Italy	46.27	9.51	0.55	1.43	29.42	0.26	0.37	47.68	8.37	0.42	1.4	25.39	0.23	0.33
Germany	41.41	12.14	0.79	2.36	27.98	0.51	0.39	39.98	11.34	0.73	2.16	28.16	0.48	0.38
Poland	45.91	10.57	0.51	1.31	37.97	0.27	0.47	46.51	9.9	0.43	1.38	34.68	0.26	0.41
Russia	43.5	12	0.58	1.9	37.52	0.49	0.32	44.43	11.38	0.49	1.95	37.63	0.47	0.3
China	41.89	13.3	0.7	2.75	38.02	0.55	0.23	43.89	10.69	0.37	2.4	38.86	0.52	0.21
Korea	40.65	13.83	0.7	3.94	20.43	0.6	0.27	42.44	12.9	0.54	3.84	20.28	0.59	0.25
Philippines	40.6	13.65	0.95	3	31.9	0.37	0.42	42.53	12.58	0.87	2.95	31.57	0.35	0.39
Vietnam	39.82	12.24	0.69	4.5	16.87	0.34	0.46	41.2	11.18	0.56	4.35	19.04	0.3	0.4
India	39.25	14.44	0.93	3.98	23.41	0.61	0.29	40.04	12.67	0.83	3.8	24.17	0.61	0.26
Africa	39.33	13.87	0.95	4.06	22.85	0.46	0.32	39.18	13.15	0.93	4.07	22.87	0.44	0.3
Middle East	39.12	12.63	0.9	2.64	36.27	0.61	0.26	39.14	11.65	0.83	2.47	37.48	0.58	0.26

*English proficiency is computed for 1980-2011 subsample due to data availability
**Net2 and Net1 denote the shares of workers in the top and middle sector respectively

	1940-2011		1980-2011	
Top sector	No	Yes	No	Yes
Age	38.35	41.03	38.24	41.16
Education	10.5	13.46	11.06	14.49
English*	0.65	0.92	0.65	0.92
Arrival year	2.63	2.97	2.72	3.07
Length of stay	35.33	31.41	36.8	32.45
Network in top sector	0.32	0.44	0.3	0.47
Network in middle sector	0.35	0.31	0.36	0.3
Middle sector	No	Yes	No	Yes
Age	38.05	38.61	37.81	38.61
Education	9.96	10.99	10.43	11.63
English	0.57	0.72	0.57	0.72
Arrival year	2.62	2.64	2.72	2.73
Length of stay	35.61	35.08	37.17	36.48
Network in top sector	0.3	0.34	0.28	0.33
Network in middle sector	0.35	0.36	0.35	0.37

Table B.15: Individual characteristic by sector

*English proficiency is computed for 1980-2011 subsample due to data availability

Figure B.3: Predicted shares from the linear probability model in the top and middle sector

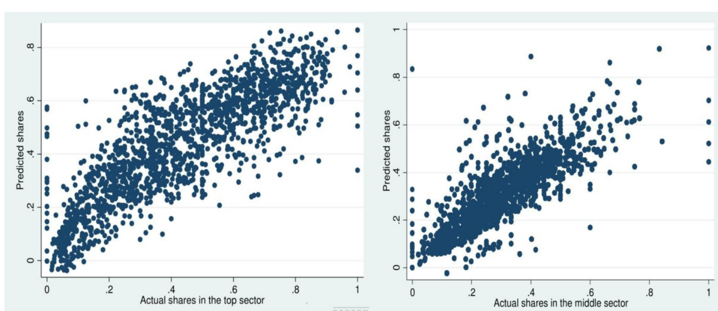

Table B.16: Individual characteristic by sector by group: unskilled workers

	Individuals in the top sector							All other individuals						
	Age	Edu	Eng*	Arr	Stay	Net2**	Net1**	Age	Edu	Eng	Arr	Stay	Net2	Net1
Canada	46.46	10.23	0.58	1.5	27.47	0.68	0.24	44.08	9.06	0.37	1.24	21.88	0.51	0.37
Mexico	35.64	9.43	0.56	2.15	44.91	0.31	0.35	34.6	8.88	0.41	2.17	44.02	0.29	0.36
Cuba	44.48	10.81	0.63	2.94	27.66	0.39	0.34	45.48	10.17	0.42	2.93	27.16	0.38	0.36
England	45.48	10.08	1	1.15	26.03	0.78	0.15	45.8	9.03	0.99	1.06	16.55	0.63	0.26
Italy	47.77	9.19	0.57	1.38	30.5	0.34	0.36	47.71	7.82	0.34	1.28	22.57	0.26	0.39
Germany	45.71	10.13	0.58	1.56	25.84	0.63	0.28	44.63	9.13	0.34	1.35	18.05	0.48	0.4
Poland	46.94	9.69	0.48	1.21	35.41	0.41	0.38	48.1	8.48	0.29	1.16	27.81	0.32	0.46
Russia	45.44	8.79	0.28	1.42	22.63	0.55	0.29	47.59	8.23	0.22	1.4	21.78	0.52	0.31
China	43.55	10.48	0.51	2.05	44.26	0.36	0.4	44.55	9.54	0.27	1.89	44.65	0.32	0.4
Korea	42.5	11.4	0.5	3.58	22.66	0.7	0.21	43.03	11.15	0.4	3.55	21.5	0.67	0.24
Philippines	38.14	11.38	0.91	2.62	35.55	0.5	0.28	41.07	10.79	0.8	2.65	31.77	0.41	0.31
Vietnam	40.3	10.61	0.6	4.4	18.01	0.49	0.41	42.07	10.11	0.45	4.44	18.57	0.43	0.46
India	39.38	11.13	0.85	3.61	26.5	0.69	0.18	40.79	10.72	0.76	3.49	27.8	0.59	0.23
Africa	38.57	11.27	0.91	3.59	26.92	0.57	0.19	39.74	11.15	0.88	3.66	27.97	0.49	0.21
Middle East	40.2	10.79	0.86	1.89	43.81	0.68	0.21	40.09	10.2	0.75	1.81	41.59	0.63	0.24
	Individuals in the middle sector							Individuals in the bottom sector						
Canada	43.97	9.02	0.35	1.22	21.53	0.5	0.38	44.28	9.13	0.4	1.27	22.54	0.53	0.35
Mexico	34.66	9.04	0.44	2.09	45.43	0.29	0.37	34.54	8.71	0.38	2.26	42.56	0.29	0.35
Cuba	45.21	10.28	0.43	2.96	27.14	0.37	0.37	45.82	10.03	0.42	2.9	27.18	0.38	0.35
England	45.91	9.16	0.99	1.08	16.94	0.63	0.27	45.63	8.83	0.99	1.03	15.96	0.63	0.25
Italy	47.16	8.05	0.37	1.28	24.32	0.27	0.4	48.31	7.57	0.3	1.28	20.64	0.26	0.38
Germany	44.73	9.09	0.33	1.34	17.61	0.47	0.42	44.44	9.2	0.37	1.35	18.9	0.5	0.37
Poland	47.91	8.5	0.29	1.16	26.89	0.32	0.47	48.43	8.46	0.31	1.16	29.37	0.32	0.44
Russia	48.2	7.98	0.19	1.36	18.81	0.52	0.32	46.6	8.65	0.28	1.46	26.65	0.53	0.28
China	44.42	9.74	0.27	2.07	46.1	0.33	0.48	44.72	9.27	0.27	1.64	42.65	0.3	0.3
Korea	43.23	11.16	0.4	3.57	22.08	0.66	0.26	42.72	11.14	0.4	3.52	20.57	0.7	0.21
Philippines	38.53	11.1	0.85	2.7	31.17	0.42	0.35	43.87	10.45	0.75	2.58	32.43	0.4	0.28
Vietnam	41.61	10.21	0.46	4.48	18.53	0.42	0.48	43.22	9.85	0.44	4.35	18.66	0.45	0.43
India	41	10.74	0.74	3.63	26.53	0.63	0.23	40.54	10.68	0.78	3.32	29.28	0.55	0.22
Africa	39.26	11.18	0.89	3.65	27.26	0.51	0.23	40.16	11.13	0.88	3.66	28.6	0.48	0.19
Middle East	40.1	10.26	0.77	1.77	42.4	0.63	0.25	40.08	10.11	0.72	1.88	40.34	0.63	0.23

*English proficiency is computed for 1980-2011 subsample due to data availability
**Net2 and Net1 denote the shares of workers in the top and middle sector respectively

Table B.17: Individual characteristic by sector: unskilled workers

	1940-2011		1980-2011	
Top sector	No	Yes	No	Yes
Age	38.24	39.95	37.59	38.9
Education	9.01	9.7	9.49	10.29
English*	0.51	0.7	0.51	0.7
Arrival year	2.17	2.23	2.31	2.35
Length of stay	38.22	38.03	41.67	40.81
Network in top sector	0.34	0.4	0.34	0.41
Network in middle sector	0.37	0.36	0.35	0.33
Middle sector	No	Yes	No	Yes
Age	38.13	38.32	37.4	37.75
Education	8.85	9.14	9.28	9.67
English	0.48	0.54	0.48	0.54
Arrival year	2.22	2.13	2.35	2.27
Length of stay	37.74	38.64	40.85	42.41
Network in top sector	0.34	0.35	0.33	0.34

*English proficiency is computed for 1980-2011 subsample due to data availability

Table B.18: Percentage of correctly predicted rankings

Top sector

	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East	0.69	0.67	0.97	0.69	0.63	0.68	0.80	0.87	0.43	0.64	0.76	1.00	1.00	0.57
Africa		0.65	0.95	0.78	0.71	0.60	0.63	0.92	0.64	0.80	0.68	1.00	0.99	0.64
India			0.98	0.83	0.74	0.70	0.71	0.89	0.47	0.77	0.65	1.00	1.00	0.67
Vietnam				0.75	0.91	0.98	0.95	0.75	1.00	0.67	1.00	0.33	0.92	0.98
Philippines					0.70	0.76	0.79	0.88	0.72	0.50	0.88	1.00	1.00	0.87
Korea						0.70	0.52	0.92	0.54	0.82	0.81	1.00	1.00	0.73
China							0.66	0.75	0.65	0.75	0.76	0.93	1.00	0.79
Russia								1.00	0.56	0.57	0.86	1.00	1.00	0.70
Poland									0.88	0.63	0.88	0.83	0.83	0.90
Germany										0.80	0.64	0.89	1.00	0.68
Italy											0.91	0.75	1.00	0.91
England												1.00	1.00	0.67
Cuba													0.88	1.00
Mexico														1.00

Middle sector

	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East	0.56	0.62	0.79	0.69	0.63	0.67	0.76	0.67	0.50	0.55	0.59	0.86	0.69	0.63
Africa		0.65	0.82	0.75	0.59	0.62	0.59	0.85	0.61	0.60	0.71	0.94	0.71	0.66
India			0.90	0.80	0.62	0.64	0.61	0.89	0.66	0.77	0.59	0.83	0.70	0.65
Vietnam				0.58	0.63	0.87	0.85	0.25	0.83	0.83	0.85	0.83	0.86	0.89
Philippines					0.53	0.75	0.75	0.75	0.84	0.70	0.76	0.73	0.76	0.87
Korea						0.66	0.67	0.58	0.79	0.73	0.73	1.00	0.68	0.73
China							0.66	0.88	0.61	0.67	0.50	1.00	0.65	0.65
Russia								0.64	0.78	0.43	0.71	1.00	0.62	0.61
Poland									0.88	0.50	0.63	1.00	0.83	0.80
Germany										0.60	0.68	0.78	0.52	0.65
Italy											0.55	0.50	0.70	0.55
England												0.91	0.74	0.52
Cuba													0.68	0.79
Mexico														0.61

Bottom sector

	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East	0.54	0.73	0.82	0.61	0.63	0.72	0.44	0.67	0.67	0.55	0.68	0.86	1.00	0.71
Africa		0.78	0.73	0.69	0.59	0.62	0.59	0.69	0.68	0.70	0.74	0.71	0.97	0.58
India			0.82	0.67	0.72	0.66	0.45	0.84	0.44	0.69	0.68	1.00	1.00	0.48
Vietnam				0.55	0.81	0.81	0.75	0.50	0.88	0.50	0.92	0.83	0.98	0.89
Philippines					0.53	0.62	0.50	0.75	0.72	0.60	0.82	0.87	0.99	0.64
Korea						0.60	0.52	0.92	0.50	0.64	0.77	0.89	1.00	0.65
China							0.55	0.81	0.71	0.75	0.71	0.93	1.00	0.70
Russia								0.73	0.56	0.57	0.64	0.60	1.00	0.57
Poland									0.88	0.50	1.00	1.00	1.00	0.90
Germany										0.90	0.41	0.89	1.00	0.48
Italy											0.82	0.63	0.90	0.82
England												0.91	1.00	0.55
Cuba													0.88	0.84
Mexico														1.00

Table B.19: Structural parameters estimates

Top sector		
Large groups		
Age	0.922	(0.287)
English proficiency	0.537	(0.542)
Arrival	0.378	(10.265)
Arrival square	1.262	(1.687)
Length of stay	1.078	(0.821)
Size of the network in top sector	1.079	(0.387)
Size of the network in middle sector	0.013	(1.650)
Others		
Age	0.494	(1.859)
Education	0.388	(4.494)
English proficiency	0.389	(1.111)
Middle sector		
Large groups		
Age	-0.417	(2.594)
English proficiency	0.102	(1.881)
Arrival	-1.919	(1.162)
Arrival square	3.557	(0.596)
Length of stay	-0.806	(1.302)
Size of the network in top sector	4.545	(0.150)
Size of the network in middle sector	2.782	(0.248)
Others		
Age	0.329	(3.502)
Education	2.711	(0.341)
English proficiency	0.240	(3.241)
σ^2_{large}	2.050	(0.667)
σ^2_{others}	1.280	(0.795)
ζ	0.966	(0.476)

Standard errors in parenthesis.

Table B.20: The effect of the 10 percent increase in the share of workers in the top sector by sector and group

Top sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.06	0.08	0.03	0.10	0.05	0.05	0.08	0.00	0.10	0.09	0.03	0.00	0.00	0.08
Africa	0.10		0.10	0.00	0.04	0.05	0.05	0.11	0.00	0.04	0.00	0.10	0.00	0.00	0.10
India	0.14	0.05		0.00	0.06	0.04	0.08	0.00	0.05	0.09	0.00	0.03	0.00	0.00	0.08
Vietnam	0.00	0.00	0.02		0.05	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Philippines	0.00	0.04	0.00	0.03		0.05	0.07	0.04	0.00	0.04	0.00	0.06	0.00	0.00	0.02
Korea	0.10	0.07	0.06	0.00	0.05		0.06	0.05	0.00	0.00	0.00	0.08	0.00	0.00	0.08
China	0.09	0.06	0.09	0.00	0.10	0.11		0.07	0.06	0.00	0.00	0.05	0.00	0.00	0.05
Russia	0.00	0.04	0.06	0.00	0.17	0.05	0.03		0.00	0.00	0.00	0.14	0.00	0.00	0.00
Poland	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.13	0.00	0.00	0.00
Germany	0.10	0.00	0.06	0.00	0.00	0.08	0.03	0.11	0.00		0.00	0.00	0.00	0.00	0.03
Italy	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.14	0.00	0.00		0.00	0.00	0.00	0.09
England	0.15	0.19	0.05	0.00	0.06	0.04	0.03	0.00	0.00	0.14	0.00		0.00	0.00	0.09
Cuba	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00		0.00	0.00
Mexico	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Canada	0.02	0.06	0.08	0.00	0.04	0.03	0.09	0.13	0.00	0.06	0.00	0.15	0.00	0.00	

Middle sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.17	0.14	0.05	0.12	0.05	0.05	0.04	0.07	0.13	0.00	0.12	0.00	0.05	0.06
Africa	0.04		0.02	0.07	0.02	0.05	0.04	0.00	0.21	0.10	0.13	0.18	0.01	0.04	0.03
India	0.06	0.06		0.06	0.04	0.06	0.09	0.03	0.05	0.09	0.15	0.00	0.09	0.02	0.08
Vietnam	0.05	0.05	0.00		0.00	0.09	0.00	0.05	0.00	0.04	0.17	0.00	0.00	0.00	0.02
Philippines	0.02	0.05	0.04	0.05		0.05	0.01	0.00	0.13	0.04	0.00	0.09	0.00	0.00	0.00
Korea	0.05	0.02	0.06	0.13	0.05		0.13	0.24	0.00	0.00	0.00	0.00	0.22	0.07	0.08
China	0.02	0.11	0.14	0.02	0.04	0.09		0.03	0.00	0.06	0.00	0.00	0.00	0.04	0.11
Russia	0.16	0.11	0.03	0.05	0.04	0.10	0.00		0.00	0.00	0.00	0.00	0.00	0.03	0.13
Poland	0.07	0.00	0.11	0.00	0.00	0.00	0.06	0.18		0.00	0.25	0.13	0.00	0.00	0.30
Germany	0.07	0.04	0.13	0.04	0.04	0.08	0.10	0.00	0.00		0.20	0.05	0.00	0.10	0.10
Italy	0.00	0.00	0.08	0.00	0.00	0.18	0.17	0.14	0.00	0.00		0.00	0.00	0.00	0.09
England	0.06	0.06	0.14	0.04	0.09	0.08	0.13	0.00	0.00	0.05	0.00		0.00	0.00	0.06
Cuba	0.00	0.06	0.00	0.00	0.20	0.11	0.00	0.00	0.33	0.11	0.00	0.00		0.04	0.00
Mexico	0.00	0.00	0.00	0.02	0.03	0.00	0.01	0.03	0.00	0.03	0.00	0.00	0.00		0.02
Canada	0.08	0.06	0.08	0.00	0.09	0.19	0.14	0.04	0.10	0.06	0.00	0.03	0.00	0.03	

Bottom sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.21	0.19	0.08	0.16	0.20	0.14	0.08	0.07	0.17	0.00	0.12	0.07	0.00	0.14
Africa	0.21		0.00	0.00	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.02
India	0.14	0.14		0.04	0.14	0.09	0.10	0.16	0.11	0.09	0.00	0.24	0.00	0.00	0.16
Vietnam	0.08	0.02	0.00		0.08	0.09	0.15	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.07
Philippines	0.04	0.05	0.07	0.03		0.09	0.06	0.13	0.06	0.08	0.00	0.15	0.00	0.00	0.04
Korea	0.22	0.10	0.15	0.06	0.16		0.21	0.00	0.00	0.25	0.09	0.19	0.00	0.00	0.08
China	0.12	0.15	0.15	0.06	0.18	0.11		0.10	0.06	0.19	0.25	0.11	0.07	0.00	0.14
Russia	0.20	0.04	0.06	0.00	0.04	0.24	0.03		0.00	0.22	0.14	0.07	0.20	0.00	0.13
Poland	0.13	0.23	0.05	0.00	0.06	0.00	0.00	0.00		0.13	0.13	0.13	0.00	0.00	0.00
Germany	0.10	0.07	0.13	0.04	0.08	0.17	0.03	0.17	0.00		0.00	0.23	0.00	0.00	0.13
Italy	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00		0.00	0.00	0.00	0.00
England	0.12	0.16	0.11	0.00	0.09	0.12	0.03	0.14	0.00	0.05	0.00		0.09	0.00	0.06
Cuba	0.00	0.06	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.16
Mexico	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Canada	0.04	0.14	0.19	0.05	0.20	0.14	0.11	0.17	0.00	0.13	0.00	0.33	0.16	0.00	

Table B.21: The effect of the 10 percent increase in the share of workers in the middle sector by sector and group

Middle sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.06	0.08	0.00	0.06	0.05	0.02	0.04	0.13	0.13	0.09	0.06	0.00	0.02	0.02
Africa	0.02		0.06	0.05	0.05	0.02	0.02	0.07	0.00	0.18	0.10	0.03	0.24	0.01	0.02
India	0.02	0.04		0.04	0.01	0.04	0.03	0.06	0.05	0.09	0.15	0.00	0.04	0.02	0.02
Vietnam	0.05	0.05	0.04		0.00	0.09	0.00	0.10	0.00	0.04	0.17	0.00	0.00	0.00	0.02
Philippines	0.06	0.04	0.04	0.18		0.14	0.04	0.08	0.19	0.04	0.00	0.09	0.00	0.04	0.02
Korea	0.02	0.05	0.02	0.06	0.05		0.09	0.19	0.00	0.00	0.00	0.08	0.22	0.05	0.03
China	0.00	0.05	0.07	0.00	0.01	0.04		0.07	0.00	0.03	0.00	0.00	0.00	0.01	0.04
Russia	0.04	0.07	0.03	0.20	0.04	0.00	0.10		0.00	0.06	0.14	0.00	0.00	0.00	0.09
Poland	0.13	0.00	0.11	0.25	0.06	0.08	0.06	0.27		0.00	0.25	0.00	0.00	0.00	0.20
Germany	0.03	0.04	0.09	0.04	0.04	0.04	0.13	0.00	0.00		0.10	0.00	0.11	0.07	0.10
Italy	0.09	0.00	0.15	0.00	0.00	0.27	0.17	0.14	0.00	0.00		0.00	0.00	0.10	0.09
England	0.00	0.00	0.05	0.08	0.06	0.04	0.03	0.14	0.00	0.00	0.00		0.00	0.00	0.06
Cuba	0.00	0.06	0.13	0.00	0.13	0.00	0.00	0.00	0.33	0.11	0.13	0.00		0.04	0.00
Mexico	0.05	0.06	0.04	0.08	0.05	0.05	0.06	0.03	0.25	0.07	0.00	0.09	0.00		0.05
Canada	0.06	0.08	0.06	0.02	0.11	0.08	0.07	0.00	0.10	0.13	0.00	0.06	0.00	0.00	

Bottom sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.04	0.08	0.00	0.02	0.02	0.05	0.00	0.07	0.07	0.00	0.03	0.00	0.00	0.02
Africa	0.06		0.03	0.00	0.00	0.00	0.02	0.04	0.08	0.00	0.00	0.03	0.00	0.00	0.00
India	0.03	0.01		0.00	0.04	0.02	0.02	0.03	0.05	0.00	0.00	0.05	0.00	0.00	0.03
Vietnam	0.05	0.07	0.00		0.13	0.13	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14
Philippines	0.06	0.04	0.06	0.08		0.09	0.08	0.13	0.00	0.04	0.00	0.12	0.00	0.00	0.07
Korea	0.10	0.05	0.04	0.00	0.00		0.13	0.00	0.00	0.21	0.09	0.08	0.00	0.00	0.03
China	0.00	0.03	0.02	0.04	0.06	0.00		0.03	0.06	0.00	0.08	0.00	0.00	0.00	0.00
Russia	0.16	0.04	0.00	0.05	0.00	0.14	0.03		0.00	0.06	0.14	0.00	0.00	0.00	0.04
Poland	0.20	0.15	0.16	0.00	0.06	0.00	0.06	0.00		0.13	0.00	0.00	0.00	0.00	0.00
Germany	0.03	0.00	0.09	0.04	0.00	0.08	0.03	0.06	0.00		0.00	0.05	0.00	0.00	0.10
Italy	0.18	0.10	0.00	0.00	0.00	0.09	0.08	0.00	0.13	0.10		0.00	0.13	0.00	0.00
England	0.00	0.03	0.05	0.00	0.03	0.04	0.00	0.14	0.00	0.05	0.00		0.00	0.00	0.06
Cuba	0.00	0.06	0.04	0.00	0.00	0.00	0.07	0.00	0.17	0.00	0.00	0.09		0.00	0.16
Mexico	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.10	0.00	0.00		0.00
Canada	0.00	0.02	0.05	0.02	0.04	0.03	0.00	0.09	0.00	0.03	0.00	0.03	0.11	0.00	

Top sector is omitted as there is barely any effect on the rankings.

Table B.22: The effect of 1 year increase in the educational attainment by sector and group

Top sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.08	0.11	0.03	0.10	0.07	0.07	0.16	0.00	0.17	0.27	0.03	0.07	0.00	0.10
Africa	0.10		0.13	0.00	0.09	0.10	0.05	0.15	0.00	0.04	0.00	0.10	0.00	0.00	0.12
India	0.14	0.08		0.00	0.06	0.06	0.06	0.10	0.05	0.13	0.00	0.03	0.00	0.00	0.10
Vietnam	0.03	0.00	0.02		0.08	0.03	0.00	0.00	0.00	0.00	0.00	0.04	0.17	0.00	0.00
Philippines	0.02	0.05	0.03	0.05		0.12	0.11	0.04	0.06	0.08	0.20	0.09	0.00	0.00	0.02
Korea	0.12	0.15	0.11	0.00	0.07		0.06	0.10	0.00	0.04	0.00	0.12	0.00	0.00	0.05
China	0.11	0.06	0.10	0.00	0.15	0.13		0.10	0.06	0.06	0.08	0.08	0.00	0.00	0.05
Russia	0.00	0.04	0.06	0.00	0.17	0.05	0.03		0.09	0.00	0.00	0.14	0.00	0.00	0.04
Poland	0.00	0.23	0.00	0.25	0.00	0.08	0.00	0.00		0.13	0.00	0.13	0.00	0.00	0.10
Germany	0.17	0.00	0.09	0.00	0.00	0.08	0.03	0.11	0.00		0.00	0.00	0.00	0.00	0.03
Italy	0.09	0.00	0.00	0.17	0.00	0.00	0.08	0.14	0.13	0.00		0.00	0.13	0.00	0.09
England	0.15	0.19	0.05	0.00	0.06	0.04	0.03	0.00	0.00	0.14	0.00		0.00	0.00	0.09
Cuba	0.07	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00		0.00	0.00
Mexico	0.00	0.00	0.00	0.06	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Canada	0.08	0.06	0.10	0.00	0.04	0.05	0.12	0.13	0.00	0.10	0.00	0.18	0.00	0.00	

Middle sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.10	0.10	0.08	0.06	0.02	0.02	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.08
Africa	0.06		0.03	0.05	0.04	0.00	0.11	0.04	0.00	0.14	0.00	0.13	0.00	0.01	0.06
India	0.08	0.04		0.06	0.04	0.04	0.09	0.03	0.00	0.13	0.08	0.03	0.00	0.03	0.05
Vietnam	0.05	0.05	0.00		0.03	0.09	0.00	0.05	0.00	0.04	0.00	0.00	0.00	0.02	0.02
Philippines	0.08	0.07	0.04	0.00		0.00	0.01	0.00	0.00	0.04	0.00	0.06	0.07	0.01	0.02
Korea	0.02	0.02	0.00	0.06	0.07		0.11	0.14	0.00	0.00	0.00	0.00	0.00	0.02	0.05
China	0.02	0.05	0.14	0.00	0.03	0.06		0.03	0.00	0.13	0.00	0.00	0.00	0.05	0.07
Russia	0.12	0.07	0.00	0.05	0.00	0.14	0.00		0.00	0.00	0.00	0.00	0.00	0.03	0.04
Poland	0.00	0.08	0.05	0.00	0.13	0.00	0.13	0.09		0.00	0.25	0.13	0.00	0.00	0.10
Germany	0.07	0.04	0.09	0.04	0.00	0.08	0.10	0.00	0.00		0.00	0.00	0.00	0.07	0.13
Italy	0.00	0.00	0.15	0.17	0.00	0.09	0.08	0.14	0.13	0.20		0.00	0.00	0.00	0.09
England	0.09	0.06	0.05	0.00	0.09	0.04	0.08	0.00	0.00	0.05	0.00		0.00	0.03	0.06
Cuba	0.00	0.06	0.00	0.00	0.13	0.11	0.00	0.00	0.33	0.00	0.00	0.00		0.00	0.00
Mexico	0.02	0.00	0.02	0.02	0.01	0.00	0.04	0.03	0.00	0.10	0.00	0.00	0.00		0.03
Canada	0.02	0.04	0.06	0.00	0.07	0.14	0.07	0.13	0.00	0.06	0.00	0.09	0.05	0.03	

Bottom sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.19	0.16	0.05	0.10	0.12	0.09	0.04	0.07	0.13	0.00	0.06	0.07	0.00	0.12
Africa	0.10		0.13	0.00	0.07	0.07	0.06	0.15	0.15	0.00	0.10	0.10	0.06	0.00	0.04
India	0.10	0.08		0.04	0.10	0.04	0.07	0.03	0.11	0.09	0.00	0.16	0.00	0.00	0.14
Vietnam	0.08	0.02	0.02		0.10	0.06	0.13	0.05	0.00	0.04	0.17	0.00	0.00	0.00	0.07
Philippines	0.06	0.05	0.10	0.05		0.12	0.07	0.17	0.00	0.12	0.00	0.15	0.00	0.00	0.04
Korea	0.17	0.07	0.13	0.06	0.14		0.19	0.00	0.00	0.25	0.09	0.19	0.00	0.00	0.05
China	0.11	0.12	0.12	0.06	0.13	0.09		0.10	0.06	0.16	0.25	0.08	0.07	0.00	0.12
Russia	0.20	0.04	0.06	0.05	0.04	0.24	0.03		0.00	0.22	0.14	0.00	0.20	0.00	0.09
Poland	0.20	0.23	0.11	0.00	0.06	0.00	0.13	0.00		0.25	0.00	0.13	0.00	0.00	0.00
Germany	0.10	0.07	0.16	0.04	0.12	0.17	0.03	0.17	0.00		0.00	0.09	0.00	0.00	0.16
Italy	0.18	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.25	0.00		0.00	0.00	0.00	0.00
England	0.12	0.13	0.03	0.00	0.09	0.08	0.03	0.00	0.00	0.00	0.00		0.09	0.00	0.03
Cuba	0.07	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.11
Mexico	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Canada	0.04	0.10	0.14	0.05	0.13	0.14	0.09	0.09	0.00	0.03	0.00	0.21	0.16	0.00	

Table B.23: The effect of English proficiency by sector and group

Top sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.04	0.03	0.03	0.06	0.00	0.04	0.08	0.00	0.03	0.09	0.03	0.00	0.00	0.04
Africa	0.02		0.04	0.00	0.00	0.00	0.03	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
India	0.05	0.01		0.00	0.03	0.00	0.00	0.00	0.05	0.00	0.00	0.03	0.00	0.00	0.03
Vietnam	0.03	0.00	0.00		0.15	0.06	0.02	0.10	0.00	0.00	0.00	0.04	0.50	0.00	0.02
Philippines	0.00	0.02	0.01	0.00		0.02	0.03	0.04	0.00	0.04	0.00	0.03	0.00	0.00	0.02
Korea	0.27	0.22	0.28	0.03	0.12		0.26	0.24	0.00	0.13	0.18	0.19	0.00	0.00	0.24
China	0.07	0.11	0.10	0.00	0.13	0.19		0.14	0.25	0.06	0.08	0.11	0.07	0.00	0.05
Russia	0.00	0.07	0.10	0.00	0.21	0.19	0.10		0.09	0.06	0.14	0.21	0.00	0.00	0.09
Poland	0.07	0.23	0.05	0.25	0.00	0.17	0.00	0.00		0.13	0.00	0.00	0.00	0.00	0.00
Germany	0.00	0.00	0.00	0.00	0.00	0.08	0.03	0.06	0.00		0.00	0.00	0.00	0.00	0.00
Italy	0.00	0.00	0.00	0.00	0.00	0.09	0.08	0.00	0.13	0.00		0.00	0.13	0.00	0.00
England	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
Cuba	0.07	0.06	0.00	0.00	0.13	0.11	0.14	0.00	0.17	0.11	0.63	0.00		0.00	0.05
Mexico	0.00	0.00	0.00	0.14	0.01	0.00	0.03	0.00	0.08	0.00	0.00	0.00	0.12		0.02
Canada	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	

Middle sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.02	0.02	0.03	0.06	0.00	0.04	0.04	0.13	0.00	0.00	0.00	0.00	0.02	0.06
Africa	0.04		0.01	0.02	0.02	0.02	0.02	0.04	0.08	0.07	0.00	0.00	0.06	0.00	0.00
India	0.03	0.05		0.02	0.04	0.04	0.03	0.00	0.05	0.06	0.08	0.03	0.04	0.02	0.06
Vietnam	0.21	0.16	0.10		0.33	0.16	0.13	0.40	0.50	0.21	0.50	0.15	0.00	0.16	0.16
Philippines	0.06	0.02	0.03	0.00		0.00	0.03	0.00	0.00	0.08	0.00	0.00	0.00	0.05	0.02
Korea	0.22	0.27	0.28	0.13	0.23		0.21	0.29	0.33	0.21	0.45	0.19	0.00	0.10	0.35
China	0.14	0.15	0.17	0.04	0.11	0.09		0.14	0.06	0.26	0.17	0.21	0.07	0.06	0.18
Russia	0.08	0.15	0.19	0.15	0.17	0.19	0.14		0.27	0.11	0.29	0.29	0.00	0.03	0.17
Poland	0.13	0.23	0.21	0.00	0.19	0.08	0.13	0.00		0.38	0.13	0.13	0.50	0.33	0.10
Germany	0.00	0.00	0.00	0.00	0.00	0.04	0.06	0.00	0.00		0.00	0.00	0.00	0.07	0.00
Italy	0.00	0.20	0.23	0.00	0.10	0.09	0.08	0.00	0.25	0.30		0.00	0.13	0.00	0.09
England	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
Cuba	0.21	0.24	0.26	0.00	0.20	0.44	0.00	0.00	0.00	0.22	0.13	0.00		0.24	0.11
Mexico	0.11	0.11	0.18	0.02	0.16	0.22	0.10	0.00	0.00	0.07	0.10	0.21	0.12		0.08
Canada	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.02	

Bottom sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.02	0.02	0.00	0.00	0.07	0.02	0.04	0.00	0.03	0.00	0.03	0.07	0.00	0.02
Africa	0.04		0.00	0.00	0.04	0.00	0.00	0.07	0.00	0.00	0.00	0.03	0.00	0.00	0.02
India	0.05	0.01		0.00	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Vietnam	0.00	0.00	0.04		0.05	0.03	0.04	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.02
Philippines	0.00	0.04	0.01	0.03		0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.07	0.00	0.04
Korea	0.12	0.02	0.11	0.06	0.07		0.15	0.00	0.00	0.13	0.09	0.12	0.00	0.00	0.11
China	0.04	0.05	0.02	0.09	0.04	0.11		0.03	0.06	0.13	0.00	0.05	0.07	0.00	0.05
Russia	0.08	0.00	0.00	0.00	0.04	0.14	0.03		0.00	0.11	0.00	0.00	0.20	0.00	0.09
Poland	0.08	1.00	0.00	0.00	0.00	0.04	0.14	0.03		0.00	0.11	0.00	0.00	0.20	0.00
Germany	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
Italy	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00		0.00	0.00	0.00	0.00
England	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
Cuba	0.14	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.16
Mexico	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Canada	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	

Table B.24: The effect of the arrival year and length of stay by sector and group

Top sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.04	0.05	0.03	0.08	0.00	0.05	0.08	0.00	0.07	0.09	0.03	0.00	0.00	0.04
Africa	0.04		0.09	0.00	0.05	0.05	0.05	0.07	0.00	0.04	0.00	0.06	0.00	0.00	0.02
India	0.10	0.04		0.00	0.04	0.04	0.05	0.00	0.05	0.03	0.00	0.00	0.00	0.00	0.05
Vietnam	0.00	0.00	0.02		0.05	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Philippines	0.00	0.02	0.00	0.05		0.02	0.07	0.04	0.00	0.04	0.00	0.03	0.00	0.00	0.02
Korea	0.07	0.05	0.06	0.00	0.05		0.06	0.05	0.00	0.00	0.00	0.08	0.00	0.00	0.05
China	0.07	0.05	0.03	0.00	0.07	0.11		0.07	0.06	0.03	0.00	0.03	0.00	0.00	0.04
Russia	0.00	0.00	0.06	0.00	0.13	0.05	0.03		0.00	0.00	0.00	0.14	0.00	0.00	0.00
Poland	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.13	0.00	0.00	0.10
Germany	0.07	0.00	0.03	0.00	0.00	0.08	0.03	0.11	0.00		0.00	0.00	0.00	0.00	0.03
Italy	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00
England	0.12	0.13	0.03	0.00	0.06	0.04	0.00	0.00	0.00	0.09	0.00		0.00	0.00	0.06
Cuba	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00		0.00	0.00
Mexico	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Canada	0.02	0.04	0.08	0.00	0.04	0.03	0.04	0.04	0.00	0.06	0.00	0.12	0.00	0.00	

Middle sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.10	0.08	0.03	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04
Africa	0.02		0.01	0.00	0.02	0.00	0.08	0.04	0.00	0.11	0.00	0.03	0.00	0.01	0.02
India	0.05	0.03		0.02	0.01	0.02	0.06	0.03	0.00	0.06	0.00	0.00	0.04	0.03	0.03
Vietnam	0.05	0.05	0.00		0.03	0.09	0.00	0.10	0.00	0.04	0.00	0.00	0.00	0.00	0.02
Philippines	0.04	0.04	0.03	0.03		0.00	0.03	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.02
Korea	0.02	0.00	0.00	0.03	0.07		0.09	0.10	0.00	0.00	0.00	0.00	0.11	0.02	0.03
China	0.00	0.03	0.08	0.00	0.01	0.06		0.00	0.00	0.06	0.00	0.00	0.00	0.04	0.07
Russia	0.16	0.07	0.00	0.05	0.00	0.10	0.00		0.00	0.00	0.14	0.00	0.00	0.03	0.04
Poland	0.00	0.08	0.05	0.00	0.06	0.00	0.13	0.09		0.00	0.13	0.13	0.00	0.00	0.10
Germany	0.03	0.04	0.09	0.00	0.00	0.04	0.10	0.00	0.00		0.00	0.00	0.00	0.07	0.10
Italy	0.00	0.00	0.15	0.00	0.00	0.18	0.08	0.14	0.00	0.10		0.00	0.00	0.00	0.09
England	0.09	0.00	0.03	0.00	0.06	0.04	0.03	0.00	0.00	0.00	0.00		0.00	0.00	0.03
Cuba	0.00	0.06	0.00	0.00	0.20	0.11	0.00	0.00	0.33	0.00	0.00	0.00		0.04	0.00
Mexico	0.02	0.00	0.00	0.02	0.04	0.00	0.05	0.03	0.00	0.07	0.00	0.00	0.00		0.03
Canada	0.02	0.02	0.06	0.00	0.07	0.08	0.04	0.04	0.10	0.10	0.00	0.03	0.00	0.03	

Bottom sector

	ME	Af	Ind	Viet	Phil	Korea	China	Rus	Pol	Ger	It	Eng	Cuba	Mex	Can
Middle East		0.08	0.11	0.03	0.08	0.07	0.07	0.04	0.07	0.10	0.00	0.06	0.07	0.00	0.08
Africa	0.10		0.10	0.00	0.04	0.00	0.03	0.11	0.15	0.00	0.00	0.06	0.06	0.00	0.04
India	0.06	0.05		0.02	0.04	0.04	0.05	0.03	0.11	0.06	0.00	0.08	0.00	0.00	0.06
Vietnam	0.03	0.00	0.00		0.08	0.06	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Philippines	0.04	0.04	0.07	0.03		0.09	0.06	0.17	0.00	0.08	0.00	0.12	0.00	0.00	0.02
Korea	0.15	0.05	0.06	0.06	0.05		0.15	0.00	0.00	0.17	0.09	0.12	0.00	0.00	0.03
China	0.04	0.06	0.08	0.04	0.11	0.06		0.10	0.06	0.10	0.08	0.03	0.07	0.00	0.11
Russia	0.16	0.04	0.06	0.05	0.04	0.24	0.03		0.00	0.11	0.14	0.00	0.00	0.00	0.09
Poland	0.13	0.23	0.05	0.00	0.00	0.00	0.00	0.00		0.13	0.00	0.13	0.00	0.00	0.00
Germany	0.07	0.07	0.09	0.04	0.04	0.17	0.00	0.00	0.00		0.00	0.09	0.00	0.00	0.13
Italy	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00		0.00	0.00	0.00	0.00
England	0.03	0.06	0.03	0.00	0.03	0.04	0.00	0.00	0.00	0.00	0.00		0.09	0.00	0.03
Cuba	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.11
Mexico	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00
Canada	0.00	0.06	0.05	0.02	0.09	0.14	0.04	0.09	0.00	0.03	0.00	0.21	0.16	0.00	

Table B.25: Placement in the empirical distribution of occupations

Top sector

	Can	Mex	Cuba	Eng	It	Ger	Pol	Rus	Chin	Kor	Phi	Vie	Ind	Af	Me
Atlanta, GA	0.27	0.07				0.20		0.27	0.27	0.20		0.07	0.27	0.20	0.27
Boston, MA	0.20	0.03		0.20	0.07	0.20		0.13	0.07	0.27		0.03	0.17	0.07	0.20
Chicago, IL	0.33	0.13				0.27	0.20	0.27	0.27	0.27	0.20		0.27	0.20	0.20
Dallas, TX	0.47	0.17							0.47	0.47	0.27	0.27	0.37	0.27	0.47
Detroit, MI	0.20	0.03				0.17		0.33	0.20				0.17	0.27	0.17
Fort Lauderdale, FL	0.07	0.03	0.07										0.17	0.17	0.13
Houston, TX	0.30	0.20	0.40			0.30			0.27	0.40	0.27	0.20	0.33	0.27	0.30
Las Vegas, NV	0.37	0.13	0.20						0.23		0.20		0.43	0.43	0.43
Los Angeles, CA	0.37	0.17	0.20	0.37		0.37		0.27	0.27	0.27	0.27	0.20	0.27	0.27	0.30
New York, NJ	0.27	0.03		0.27	0.20	0.27	0.13	0.20	0.20	0.20	0.13	0.10	0.13	0.13	0.20
Nassau Co, NY		0.03							0.07	0.07	0.03		0.07	0.07	0.07
Bergen, NJ		0.07					0.13	0.33		0.20	0.17		0.27	0.37	0.20
Jersey City, NJ		0.07	0.17						0.40		0.20		0.27	0.27	
Middlesex, NJ		0.03						0.07	0.17		0.07		0.13	0.10	
Newark, NJ		0.03							0.20		0.07		0.20	0.07	
Philadelphia, PA	0.20	0.03		0.13				0.07	0.07	0.07	0.03	0.03	0.07	0.03	0.27
Riverside,CA	0.43	0.20							0.47	0.37	0.27		0.47	0.53	
San Diego, CA	0.27	0.13				0.20		0.40	0.27	0.27	0.13	0.20	0.27	0.27	0.27
San Francisco, CA	0.40	0.10		0.40		0.40		0.27	0.20		0.17	0.13	0.20		0.20
Oakland, CA		0.07				0.37		0.37	0.27	0.27	0.17	0.20	0.27	0.27	0.37
San Jose, CA	0.17	0.03				0.27		0.17	0.13	0.10	0.03	0.03	0.13	0.27	0.20
Seattle-Everett, WA	0.33	0.17						0.27	0.30	0.27	0.20	0.20	0.30	0.20	0.47
Washington, DC	0.20	0.03		0.13		0.10		0.20	0.07	0.07	0.07	0.03	0.07	0.07	0.13

Middle sector

	Can	Mex	Cuba	Eng	It	Ger	Pol	Rus	Chin	Kor	Phi	Vie	Ind	Af	Me
Atlanta, GA	0.40	0.30				0.43		0.43	0.37	0.37		0.40	0.37	0.37	0.40
Boston, MA	0.30			0.33	0.20	0.30		0.30	0.30	0.27		0.30	0.37	0.30	0.33
Chicago, IL	0.33	0.30				0.40	0.37	0.33	0.30	0.37	0.40		0.37	0.37	0.37
Dallash, TX	0.30	0.33							0.30	0.30	0.43	0.40	0.33	0.37	0.30
Detroit, MI	0.30					0.30		0.23	0.40				0.37	0.30	0.30
Fort Lauderdale, FL	0.40	0.23	0.33										0.40	0.40	0.40
Houston, TX	0.37	0.33	0.30			0.37			0.33	0.30	0.40	0.43	0.37	0.40	0.37
Las Vegas, NV	0.30	0.37	0.53						0.50		0.37		0.33	0.33	0.33
Los Angeles, CA	0.27	0.30	0.37	0.30		0.30		0.30	0.30	0.33	0.33	0.40	0.33	0.33	0.30
New York, NJ	0.37	0.30		0.37	0.37	0.37	0.33	0.37	0.33	0.40	0.40	0.40	0.33	0.33	0.40
Nassau Co, NY									0.33	0.37	0.30		0.33	0.37	0.37
Bergen, NJ							0.17	0.23		0.30	0.30		0.27	0.20	0.30
Jersey City, NJ		0.23	0.30						0.20		0.37		0.30	0.33	
Middlesex, NJ								0.33	0.43		0.40		0.40	0.33	
Newark, NJ		0.30							0.37		0.50		0.40	0.37	
Philadelphia, PA	0.37	0.13		0.43				0.37	0.37	0.40	0.60	0.37	0.43	0.40	0.37
Riverside,CA	0.30	0.33							0.30	0.33	0.40		0.30	0.27	
San Diego, CA	0.40	0.30				0.43		0.33	0.40	0.40	0.43	0.43	0.40	0.40	0.40
San Francisco, CA	0.20	0.17		0.20		0.20		0.33	0.30		0.33	0.33	0.33		0.43
Oakland, CA		0.23				0.23		0.23	0.30	0.40	0.37	0.30	0.30	0.30	0.23
San Jose, CA	0.43	0.07				0.33		0.53	0.43	0.43	0.33	0.33	0.43	0.37	0.43
Seattle-Everett, WA	0.23							0.20	0.23	0.27	0.30	0.30	0.23	0.23	0.20
Washington, DC	0.37	0.13		0.40		0.33		0.40	0.33	0.33	0.33	0.33	0.33	0.30	0.30

Table B.26: Rankings of new cohorts of immigrant workers

	T	M	B		T	M	B		T	M	B
New York, NY				*Chicago, IL*				*Philadelphia, PA*			
Canada	0.27	0.37	0.36	Canada	0.33	0.33	0.34	Canada	0.27	0.33	0.4
England	0.27	0.37	0.36	Germany	0.28	0.4	0.32	Middle East	0.27	0.33	0.4
Germany	0.27	0.37	0.36	China	0.26	0.3	0.44	England	0.2	0.43	0.37
Italy	0.2	0.37	0.43	India	0.26	0.37	0.37	Russia	0.1	0.36	0.54
Russian	0.2	0.37	0.43	Korea	0.26	0.37	0.37	India	0.1	0.43	0.47
China	0.2	0.33	0.47	Russia	0.26	0.33	0.41	Korea	0.1	0.36	0.54
Korea	0.2	0.4	0.4	Africa	0.2	0.33	0.47	China	0.07	0.33	0.6
Middle East	0.2	0.37	0.43	Middle East	0.2	0.37	0.43	Africa	0.07	0.4	0.53
Poland	0.16	0.33	0.51	Philippines	0.2	0.4	0.4	Philippines	0.07	0.56	0.37
Philippines	0.13	0.4	0.47	Poland	0.2	0.37	0.43	Vietnam	0.03	0.33	0.64
Vietnam	0.13	0.4	0.47	Mexico	0.13	0.3	0.57	Mexico	0.03	0.13	0.84
India	0.13	0.33	0.54								
Africa	0.13	0.33	0.54								
Mexico	0.04	0.3	0.66								
San Francisco, CA				*Dallas, TX*				*Bergen, NJ*			
Canada	0.43	0.2	0.37	Canada	0.46	0.3	0.24	Africa	0.4	0.2	0.4
England	0.43	0.2	0.37	Middle East	0.46	0.3	0.24	Russia	0.36	0.2	0.44
Germany	0.43	0.2	0.37	China	0.46	0.3	0.24	Korea	0.27	0.27	0.46
Russia	0.26	0.33	0.41	Korea	0.46	0.3	0.24	India	0.27	0.27	0.46
Middle East	0.26	0.37	0.37	India	0.37	0.33	0.3	Philippines	0.2	0.3	0.5
China	0.2	0.3	0.5	Philippines	0.27	0.43	0.3	Middle East	0.2	0.3	0.5
Philippines	0.2	0.3	0.5	Vietnam	0.27	0.4	0.33	Poland	0.13	0.13	0.74
India	0.2	0.3	0.5	Africa	0.27	0.37	0.36	Mexico	0.07	0	0.93
Vietnam	0.16	0.33	0.51	Mexico	0.17	0.3	0.53				
Mexico	0.13	0.13	0.74								
Columbus, OH				*Minneapolis,MN*				*Orlando, FL*			
China	0.36	0.3	0.34	China	0.4	0.23	0.37	England	0.27	0.3	0.43
India	0.2	0.5	0.3	India	0.4	0.23	0.37	Africa	0.27	0.3	0.43
Mexico	0.07	0	0.93	Africa	0.2	0.33	0.47	India	0.2	0.4	0.4
Africa	0.03	0.3	0.67	Mexico	0.07	0.3	0.63	Philippines	0.07	0.43	0.5
								Cuba	0.03	0.33	0.64
								Mexico	0.03	0.3	0.67

Table B.27: Rankings of "more" skilled new cohorts of immigrant workers

	T	M	B		T	M	B		T	M	B
New York, NY				*Chicago, IL*				*Philadelphia, PA*			
Canada	0.27	0.37	0.36	Canada	0.4	0.3	0.3	Canada	0.27	0.33	0.4
Eng;and	0.27	0.37	0.36	Germany	0.27	0.4	0.33	Middle East	0.27	0.33	0.4
Italy	0.27	0.33	0.4	Poland	0.27	0.33	0.4	England	0.24	0.43	0.33
Germany	0.27	0.37	0.36	Russia	0.27	0.33	0.4	Russia	0.17	0.37	0.46
Korea	0.27	0.37	0.36	China	0.27	0.33	0.4	China	0.17	0.37	0.46
Middle East	0.27	0.33	0.4	Korea	0.27	0.37	0.36	Korea	0.17	0.37	0.46
Russia	0.27	0.33	0.4	India	0.27	0.37	0.36	Philippines	0.17	0.53	0.3
China	0.23	0.37	0.4	Africa	0.27	0.33	0.4	India	0.17	0.4	0.43
Poland	0.17	0.37	0.46	Middle East	0.27	0.33	0.4	Africa	0.17	0.33	0.5
Philippines	0.17	0.4	0.43	Philippines	0.23	0.4	0.37	Vietnam	0.1	0.37	0.53
Vietnam	0.17	0.4	0.43	Mexico	0.17	0.37	0.46	Mexico	0.07	0.13	0.8
India	0.17	0.37	0.46								
Africa	0.17	0.36	0.47								
Mexico	0.13	0.3	0.57								
San Francisco, CA				*Dallas, TX*				*Bergen, NJ*			
Canada	0.47	0.23	0.3	Canada	0.47	0.27	0.26	Africa	0.47	0.23	0.3
England	0.47	0.23	0.3	Korea	0.47	0.27	0.26	Russia	0.43	0.17	0.4
Germany	0.47	0.23	0.3	China	0.47	0.27	0.26	Korea	0.27	0.33	0.4
Russia	0.33	0.3	0.37	Middle East	0.47	0.27	0.26	India	0.27	0.33	0.4
India	0.27	0.33	0.4	India	0.43	0.3	0.27	Middle East	0.27	0.27	0.46
Middle East	0.27	0.37	0.36	Philippines	0.3	0.4	0.3	Philippines	0.23	0.37	0.4
China	0.27	0.3	0.43	Africa	0.3	0.33	0.37	Poland	0.17	0.13	0.7
Philippines	0.23	0.37	0.4	Vietnam	0.27	0.4	0.33	Mexico	0.17	0	0.83
Vietnam	0.16	0.37	0.47	Mexico	0.17	0.36	0.47				
Mexico	0.16	0.13	0.71								
Columbus, OH				*Minneapolis,MN*				*Orlando, FL*			
China	0.43	0.23	0.34	China	0.43	0.23	0.34	England	0.27	0.33	0.4
India	0.27	0.43	0.3	India	0.43	0.23	0.34	Africa	0.27	0.33	0.4
Mexico	0.17	0.03	0.5	Africa	0.23	0.37	0.4	India	0.23	0.4	0.37
Africa	0.13	0.37	0.8	Mexico	0.16	0.37	0.46	Philippines	0.17	0.47	0.36
								Cuba	0.13	0.37	0.5
								Mexico	0.07	0.3	0.63

Appendix C

Estimation Details for Chapter 2

This section outlines the two step procedure employed to estimate the model. First, regress $eduf_{ij}$ on X_{ij} and $ed\bar{u}_{ij}$ on X_{ij} and obtain α^f and α^{av}. Then define the residuals from these two regressions as follows:

$$\begin{aligned}
\hat{v^f}_{ij} &= eduf_{ij} - X_{ij}\hat{\alpha^f} \\
v^{\hat{a}v}_{ij} &= ed\bar{u}_{ij} - X_{ij}\alpha^{\hat{a}v}
\end{aligned} \tag{C.1}$$

The conditional variances of the father's education and average education errors can be estimated using both parametric and non-parametric methods. In this paper I employ parametric approach and assume the following functional form of the heteroskedasticity:

$$\begin{aligned}
H_{ij}^{v^f} &= \exp(Z_{ij}\theta^f) \\
H_{ij}^{v^{av}} &= \exp(Z_{ij}\theta^{av})
\end{aligned} \tag{C.2}$$

where Z_{ij} is a vector of variables responsible for the heteroskedasticty of the errors. Note that there are no restrictions imposed over the relationship between Z_{ij} and X_ij, i.e. model is identified even if $Z_{ij} = X_{ij}$. If, however, there are variables that appear in Z_{ij} but not in X_{ij}, they do not help identify the model in a standard way. Since it is the movement in the variances that grants identification in the model, variables in Z_{ij} aid identification only if they can explain the differences in the variance across observations.

The conditional variances are estimated using non linear least squares using $\ln(\hat{v}_{ij}^{f})$ and $\ln(\hat{v}_{ij}^{av})$ as dependent variables. Then we can compute the standard deviation of the error terms associated with the two reduced forms: $\hat{H}_{v^f ij} = \sqrt{\exp(Z_{v^f ij}\hat{\theta^f})}$ and $\hat{H}_{v^{av} ij} = \sqrt{\exp(Z_{v^{av} ij}\hat{\theta^{av}})}$.

Last element needed to estimate the parameters of the main equation is the standard deviation of the child's education error (so the error term of the main equation). Since consistent residuals are nor readily available, it is estimated simultaneously with the parameters of the main equation in an iterative procedure. Let $\beta = \{\gamma_1, \gamma_2, \delta_0, \theta_u\}$. The parameters are found using a non linear least squares:

$$\min_{\beta,\rho_1,\rho_2} \sum_{i=1}^{n} \left(edu_{ij} - \gamma_1 eduf_{ij} - \gamma_2 ed\bar{u}_{ij} - \delta_0 X_{ij} - \rho_1 \frac{H_{uij}}{\hat{H}_{v^f ij}} \hat{v}_{ij}^{f} - \rho_2 \frac{H_{uij}}{\hat{H}_{v^{av} ij}} \hat{v}_{ij}^{av} \right)^2$$

where H_{uij} denotes the conditional variance of the child's education equation. In a fully parametric specification, assume $H_{uij}^2 = exp(z_{uij}\theta_u)$.

To simplify the computations, Klein and Vella (2010) suggest a two step procedure. First, for a given value of $\beta = \tilde{\beta}$, compute the residuals $\hat{u_{ij}}$ and compute the standard deviation of the child's education error in the same way as $\hat{H}_{v^f ij}$ and $\hat{H}_{v^{av} ij}$, so $\hat{H}_{u_{ij}} = \sqrt{\exp(Z_{uij}\tilde{\theta}_u)}$. Second, estimate ρ_1 and ρ_2 by minimizing the sum of the squared residuals of the child's education equation:

$$\min_{\rho_1,\rho_2} \sum_{i=1}^{n} \left(u_{ij}(\tilde{\beta}) - \rho_1 \frac{\hat{H}_u(\tilde{\beta})}{\hat{H}_{v^f}} \hat{v}_{ij}^{f} - \rho_2 \frac{\hat{H}_u(\tilde{\beta})}{\hat{H}_{v^{av}}} \hat{v}_{ij}^{av} \right)^2 \tag{C.3}$$

Repeat the last two steps until the minimum of (C.3) is found.

Appendix D

Tables for Chapter 2

Table D.1: Summary statistics

Country of ancestry	1977-2010	1977-1989	1990-2010
Africa	0.08		0.14
Austria	0.51	0.7	0.38
French Canada	1.48	1.58	1.42
Other Canada	0.56	0.65	0.49
China	0.2	0.1	0.27
Czechoslovakia	1.85	1.94	1.79
Denmark	0.89	0.98	0.83
England and Wales	17.16	18.63	16.15
Finland	0.45	0.55	0.38
France	2.67	2.74	2.63
Germany	24.63	25.3	24.18
Greece	0.42	0.31	0.5
Hungary	0.64	0.75	0.56
Ireland	16.5	15.7	17.04
Italy	7.34	6.98	7.59
Japan	0.15	0.14	0.16
Mexico	3.35	2.52	3.91
Netherlands	2.21	2.35	2.11
Norway	2.59	2.83	2.43
Philippines	0.2	0.05	0.3
Poland	3.8	3.94	3.7
Puerto Rico	0.64	0.33	0.86
Russia	1.75	1.54	1.9
Scotland	4.56	3.91	5
Spain	0.9	0.87	0.91
Sweden	2.3	2.47	2.18
Switzerland	0.44	0.58	0.34
India	0.07		0.12
Portugal	0.19	0.1	0.25
Yugoslavia	0.42	0.51	0.36
Arabic	0.05	0.05	0.05
American only	0.99	0.89	1.05

Table D.2: Summary statistics

	1977-2010			1977-1989	1990-2010
	All	Men	Women	All	All
Female	0.53			0.54	0.53
	(0.50)			(0.50)	(0.50)
Age	40.15	39.98	40.29	38.06	41.57
	(12.26)	(12.24)	(12.29)	(12.37)	(11.98)
Number of siblings	3.08	3.02	3.13	3.28	2.94
	(2.26)	(2.23)	(2.28)	(2.38)	(2.16)
Years of schooling	13.95	14.04	13.87	13.43	14.31
	(2.63)	(2.77)	(2.50)	(2.61))	(2.59)
Parental capital	11.63	11.68	11.59	10.81	12.19
	(3.94)	(3.97)	(3.92)	(3.98)	(3.82)
Ethnic capital	11.47	11.52	11.42	10.86	11.90
	(1.78)	(1.77)	(1.78)	(1.77)	(1.66)
Living in a city	0.42	0.42	0.43	0.40	0.43
at the age of 16	(0.49)	(0.49)	(0.49)	(0.49)	(0.50)
Living in a Southern	0.25	0.25	0.25	0.24	0.25
state at the age of 16	(0.43)	(0.4)3	(0.43)	(0.43)	(0.43)
At least one parent	0.10	0.09	0.10	0.11	0.09
born abroad	(0.30)	(0.29)	(0.30)	(0.31)	(0.29)
Number of observations	14366	6722	7644	5834	8532

Standard deviations in brackets.

Table D.3: Self, parental and ethnic capital by ancestry

Country of ancestry	Self	Father	Ethnic capital	Sample size
Africa	12.83	12.42	11.39	12
Austria	14.10	10.84	11.00	73
French Canada	13.15	10.38	10.03	213
Other Canada	13.73	11.56	11.26	80
China	15.03	12.90	12.77	29
Czechoslovakia	13.70	10.86	11.10	266
Denmark	14.47	11.51	11.32	128
England and Wales	14.45	12.30	12.17	2465
Finland	13.88	11.30	11.00	64
France	13.90	11.95	11.87	384
Germany	13.77	11.57	11.52	3539
Greece	14.77	12.18	11.20	61
Hungary	14.34	11.67	11.30	92
Ireland	13.88	11.83	11.68	2370
Italy	14.01	11.21	11.06	1055
Japan	14.82	12.36	12.90	22
Mexico	12.43	7.74	6.80	481
Netherlands	13.21	11.12	11.18	317
Norway	13.79	11.86	11.72	372
Philippines	14.00	13.24	13.32	29
Poland	14.02	11.37	11.16	546
Puerto Rico	13.12	10.02	9.58	92
Russia	15.48	13.17	12.91	252
Scotland	14.51	12.58	12.35	655
Spain	13.87	10.79	10.46	129
Sweden	14.25	12.45	12.35	330
Switzerland	14.46	12.75	12.51	63
India	14.40	14.60	14.28	10
Portugal	14.48	11.85	10.11	27
Yugoslavia	13.87	11.48	11.64	61
Arabic	15.29	14.00	13.62	7
American only	12.49	10.17	9.61	142

Table D.4: Self, parental and ethnic capital by origin and cohort

Country of ancestry	Cohort 1 Self edu	Cohort 1 Father edu	Cohort 1 Ethnic capital	Cohort 2 Self edu	Cohort 2 Father edu	Cohort 2 Ethnic capital	Cohort 3 Self edu	Cohort 3 Father edu	Cohort 3 Ethnic capital	Cohort 4 Self edu	Cohort 4 Father edu	Cohort 4 Ethnic capital
Africa							12.50	12.17	10.42	13.17	12.67	12.36
Austria	12.15	6.08	7.40	14.67	9.81	10.11	14.39	13.55	13.15			
French Canada	11.95	8.00	6.96	12.74	9.76	9.43	13.62	11.15	10.90			
Other Canada				13.59	11.66	11.04	13.80	11.51	11.38			
China							14.73	11.80	12.48	15.36	14.07	13.09
Czechoslovakia	11.00	5.43	7.31	13.74	9.31	9.49	14.06	12.18	12.17	14.21	14.57	14.70
Denmark	13.40	8.45	8.72	14.85	10.43	10.42	14.56	13.04	12.63			
England and Wales	13.20	9.70	9.69	14.53	11.37	11.18	14.59	13.20	13.14	14.65	14.65	14.40
Finland				13.49	10.40	10.41	14.34	12.38	11.71			
France	12.75	8.55	8.68	13.95	10.74	10.85	13.97	12.47	12.36	14.00	14.02	13.59
Germany	12.14	8.39	8.36	13.63	10.18	10.11	13.94	12.29	12.27	14.24	13.65	13.57
Greece				13.31	9.00	8.68	15.29	13.31	12.10			
Hungary				14.10	9.87	9.93	14.46	12.59	12.00			
Ireland	12.56	8.81	8.62	13.68	10.41	10.30	14.10	12.63	12.48	14.25	13.92	13.71
Italy	11.38	5.89	5.95	14.00	9.91	9.58	14.28	12.04	11.98	14.24	13.28	13.14
Japan							14.82	12.36	12.90			
Mexico	9.18	3.09	3.53	10.95	5.22	5.28	12.60	7.91	6.77	13.30	9.32	7.94
Netherlands	11.00	8.03	7.77	13.10	9.68	9.81	13.57	12.01	12.07	13.77	13.38	13.49
Norway	12.58	8.75	8.44	13.57	10.61	10.56	13.93	12.55	12.38	14.50	14.25	14.12
Philippines				13.00	0.00	10.98	13.30	13.20	13.26	14.44	14.00	13.48
Poland	12.58	6.92	6.88	13.75	9.74	9.48	14.23	12.19	12.05	14.46	14.26	13.84
Puerto Rico				10.78	8.11	6.73	13.12	9.57	9.00	14.04	11.96	12.21
Russia	15.36	8.00	6.93	15.30	11.91	11.32	15.62	14.09	14.08	15.52	16.04	16.07
Scotland	13.68	11.36	10.43	14.56	11.52	11.14	14.59	13.09	13.10	14.64	14.43	14.11
Spain				13.47	8.41	9.06	14.04	11.35	10.70	13.87	13.20	12.38
Sweden	13.10	9.25	9.09	14.47	11.27	11.13	14.28	13.07	12.98	14.15	14.53	14.53
Switzerland				13.96	11.48	11.03	14.75	13.48	13.35			
India				12.00	10.00	11.77	18.00	19.00	14.03	13.71	14.00	14.72
Portugal							14.48	11.85	10.11			
Yugoslavia				13.92	9.32	9.39	13.83	12.97	13.20			
Arabic							15.29	14.00	13.62			
American only	9.27	7.18	6.44	12.53	9.00	7.47	12.81	10.72	10.28	12.89	11.39	11.80

Cohort 1,2,3 and 4 include individuals born between 1913-1929, 1930-1949, 1950-1969, 1970-1992 respectively

Table D.5: Conditional probabilities of obtaining at most high school or above high school education

	Father's education					
	1977-2010		1977-1989		1990-2010	
	Above HS	HS or less	Above HS	HS or less	Above HS	HS or less
Self education						
Above HS	0.84	0.49	0.79	0.41	0.86	0.56
HS or less	0.16	0.51	0.21	0.59	0.13	0.44
	Average education of ethnic group					
	1977-2010		1977-1989		1990-2010	
	Above HS	HS or less	Above HS	HS or less	Above HS	HS or less
Self education						
Above HS	0.66	0.54	0.56	0.47	0.71	0.62
HS or less	0.34	0.46	0.44	0.53	0.29	0.38

Table D.6: Parental and ethnic capital - conditional means

	1977-2010		1977-1989		1990-2010	
	Parental capital	Ethnic capital	Parental capital	Ethnic capital	Parental capital	Ethnic capital
Age	-0.091	-0.033	-0.208	-0.097	-0.31	-0.022
	(0.016)	(0.006)	(0.025)	(0.009)	(0.021)	(-.005)
Living in a city	1.216	-0.032	1.206	-0.062	1.260	0.033
at the age of 16	(0.061)	(0.022)	(0.097)	(0.032)	(0.076)	(0.017)
Living in a Southern	-0.785	0.008	-0.903	0.034	-0.788	-0.006
state at the age of 16	(0.113)	(0.039)	(0.187)	(0.065)	(0.133)	(0.030)
Number of siblings	-0.311	-0.083	-0.3275	-0.084	-0.258	-0.008
	(0.014)	(0.006)	(0.021)	(0.008)	(0.018)	(0.004)
Father born abroad	-2.441		- 2.300		-1.451	
	(0.141)		(190)		(0.164)	
At least one parent		-1.214		-0.941		-0.092
born abroad		(0.057)		(0.074)		(0.032)
Constant	12.298	13.012	14.875	14.32	13.210	12.997
	(0.385)	(0.136)	(0.559)	(0.179)	(1.089)	(0.241)
Breush-Pagan test	501.38	517.75	156.16	164.49	281.33	997.14
White test	1008.40	1003.7	449.32	457.64	1084.63	2469.24
Number of observations	14366		5834		8532	

Robust standard errors in brackets.
All regressions also include age squared, dummy variables for region of residence and year dummies for cross section.

Table D.7: Heteroskedastic indexes for parental and ethnic capital

	All		1977-1989		1990-2010	
	Parental capital	Ethnic capital	Parental capital	Ethnic capital	Parental capital	Ethnic capital
Age	-0.005	-0.795	-0.021	-0.850	0.005	-0.802
	0.01	(0.053)	(0.011)	(0.030)	(0.012)	(1.083)
Living in a city at the age of 16	0.245			-0.322	0.269	
	(0.035)			(0.105)	(0.041)	
Living in a Southern state at the age of 16	0.273		0.355		0.198	
	(0.030)		(0.061)		(0.048)	
Number of siblings	0.035		0.021		0.038	
	(0.008)		(0.015)		(0.008)	
At least one parent born abroad		0.673		0.352		0.086
		(0.218)		(0.181)		(0.149)
Father born abroad	0.383		0.307		0.492	
	(0.045)		(0.065)		(0.053)	
Year dummies	Yes	Yes	No	Yes	Yes	Yes
Regional dummies	No	Yes	No	Yes	No	Yes
Constant	0.375	14.038	0.594	14.643	0.561	14.439
	(0.26)	0.760	(0.225)	(0.404)	(0.256)	(12.739)

Standard errors bootstrapped

Table D.8: Hetersoskedastic index for children capital

	1977-2010	1977-1989	1990-2010
Female	-0.462	-1.230	-0.243
	(0.076)	(0.281)	(0.090)
Number of siblings	-0.095		-0.061
	(0.023)		(0.023)
Age	0.217	0.307	0.172
	(0.033)	0.064	(0.031)
Constant	-5.629	-7.504	-4.495
	(0.753)	(1.297)	(0.704)

Standard errors bootstrapped,

Table D.9: Relationship between parental and ethnic capital and children education

	1977-2010		1977-1989		1990-2010	
	OLS	CF	OLS	CF	OLS	CF
Parental capital	0.247	0.190	0.238	0.171	0.252	0.206
	(0.006)	(0.005)	(0.009)	(0.011)	(0.007)	(0.008)
Ethnic capital	0.108	0.049	0.150	0.120	0.079	0.008
	(0.016)	(0.022)	(0.026)	(0.032)	0.020	(0.020)
Female	-0.144	-0.158	-0.367	-0.395	0.001	-0.009
	(0.038)	(0.041)	(0.059)	(0.062)	0.050)	(0.054)
Age	0.218	0.258	0.269	0.301	0.192	0.239
	(0.011)	(0.009)	(0.017)	(0.015)	(0.015)	(0.015)
Living in a city at the age of 16	0.301	0.387	0.307	0.413	0.291	0.353
	(0.040)	(0.043)	(0.063)	(0.062)	(0.052)	(0.054)
Living in a Southern	-0.123	-0.164	-0.270	-0.331	-0.042	-0.066
state at the age of 16	(0.071)	(0.066)	(0.115)	(0.088)	(0.090)	(0.096)
Number of siblings	-0.161	-0.184	-0.168	-0.186	-0.151	-0.174
	(0.009)	(0.009)	(0.013)	(0.016)	(0.012)	(0.013)
At least one parent born abroad	0.467	0.249	0.372	0.171	0.589	0.380
	(0.069)	(0.072)	(0.102)	(0.121)	(0.093)	(0.097)
ρ_1		0.102		0.147		0.075
		(0.008)		(0.010)		(0.012)
ρ_2		0.017		0.009		0.019
		(0.003)		(0.005)		(0.004)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.367	5.790	4.361	4.796	6.216	6.639
	(0.321)	(0.352)	(0.509)	(0.417)	(0.417)	(0.410)

Standard errors bootstrapped

Table D.10: Heteroskedastic indexes for parental and ethnic capital with all variables in the index 1977-2010

	Parental capital	Ethnic capital
Age	-0.005	-0.795
	0.01	(0.048)
Living in a city at the age of 16	0.236	-0.198
	(0.035)	(0.126)
Living in a Southern	0.189	-0.036
state at the age of 16	(0.065)	(0.185)
Number of siblings	0.036	0
	(0.006)	(0.021)
At least one parent born abroad		0.673
		(0.218)
Father born abroad	0.380	
	(0.044)	
Year dummies	Yes	Yes
Regional dummies	Yes	Yes
Constant	0.469	14.035
	(0.255)	(0.697)

Standard errors bootstrapped

Table D.11: Hetersoskedastic index for children capital with all variables in heteroskedasticity index 1977-2010

Age	0.217
	(0.027)
Living in a city at the age of 16	-0.106
	(0.062)
Living in a Southern	-0.264
state at the age of 16	(0.137)
Number of siblings	-0.102
	(0.025)
At least one parent born abroad	0.242
	-0.141
Year dummies	Yes
Regional dummies	Yes
Constant	-5.556
	(0.661)

Standard errors bootstrapped

Table D.12: Relationship between parental and ethnic capital and children education with all variables in the heteroskedastic index 1977-2010

	1977-2010	
	OLS	CF
Parental capital	0.247	0.207
	(0.006)	(0.007)
Ethnic capital	0.108	0.058
	(0.016)	(0.020)
Female	-0.144	-0.154
	(0.038)	(0.045)
Age	0.218	0.248
	(0.011)	(0.011)
Living in a city at the age of 16	0.301	0.360
	(0.040)	(0.038)
Living in a Southern state at the age of 16	-0.123	-0.154
	(0.071)	(0.066)
Number of siblings	-0.161	-0.178
	(0.009)	(0.009)
At least one parent born abroad	0.467	0.307
	(0.069)	(0.081)
ρ_1		0.071
		(0.011)
ρ_2		0.013
		(0.003)
Year dummies	Yes	Yes
Region dummies	Yes	Yes
Constant	5.367	5.714
	(0.321)	(0.327)

Standard errors bootstrapped

Table D.13: Conditional means for parental and ethnic capital by gender 1977-2010

	Men		Women	
	Parental capital	Ethnic capital	Parental capital	Ethnic capital
Age	-0.070	-0.038	-0.107	-0.027
	(0.024)	(0.009)	(0.023)	(0.009)
Living in a city at the age of 16	1.227	-0.002	1.207	-0.059
	(0.089)	(0.031)	(0.083)	(0.031)
Living in a Southern state at the age of 16	-0.842	-0.066	-0.732	0.067
	(0.168)	(0.059)	(0.153)	(0.052)
Number of siblings	-0.319	-0.082	-0.305	-0.083
	(0.020)	(0.008)	(0.020)	(0.008)
Father born abroad	-2.380		-2.488	
	(0.208)		(0.192)	
At least one parent born abroad		-1.241		-1.188
		(0.085)		(0.078)
Constant	12.216	13.255	12.364	12.774
	(0.556)	(0.194)	(0.535)	(0.190)
Breush-Pagan test	247.64	2741.55	277.86	2844.84
White test	686.18	1550.65	767.16	1596.14
Number of observations	6722		7644	

Robust standard errors in brackets

Table D.14: Hetersoskedastic index for parental and ethnic capital by gender 1977-2010

	Men		Women	
	Parental capital	Ethnic capital	Parental capital	Ethnic capital
Age	-0.007	-0.924	-0.007	-0.768
	(0.012)	(0.035)	(0.006)	(0.014)
Living in a city at the age of 16	0.251		0.189	
	(0.070)		(0.037)	
Living in a Southern state at the age of 16	0.295		0.193	
	(0.060)		(0.101)	
Number of siblings	0.047	0.035	0.022	
	(0.009)	(0.030)	(0.008)	
At least one parent born abroad		0.268		0.812
		(0.142)		(0.127)
Father born abroad	0.325		0.465	
	(0.075)		(0.060)	
Year dummies	Yes	No	Yes	No
Regional dummies	No	Yes	Yes	Yes
Constant	0.313	14.741	0.743	13.445
	(0.291)	(0.468)	(0.138)	(0.247)

Standard errors bootstrapped

Table D.15: Hetersoskedastic index for children capital by gender 1977-2010

	Men	Women
Number of siblings	-0.035	-0.309
	(0.023)	(0.051)
Age	0.217	0.219
	(0.030)	(0.057)
Year dummies	Yes	No
Region dummies	No	Yes
Constant	-5.903	-5.456
	(0.659)	(1.215)

Standard errors bootstrapped

Table D.16: Relationship between parental and ethnic capital and children education by gender 1977-2010

	Men		Women	
	OLS	CF	OLS	CF
Parental capital	0.257	0.163	0.237	0.213
	(0.009)	(0.007)	(0.007)	(0.006)
Ethnic capital	0.081	0.016	0.133	0.079
	(0.025)	(0.027)	(0.020)	(0.023)
Age	0.253	0.306	0.183	0.212
	(0.017)	(0.017)	(0.014)	(0.011)
Living in a city at the age of 16	0.442	0.581	0.183	0.226
	(0.063)	(0.047)	(0.014)	(0.037)
Living in a Southern	-0.186	-0.256	-0.062	-0.079
state at the age of 16	(0.112)	(0.086)	(0.089)	(0.070)
Number of siblings	-0.164	-0.196	-0.158	-0.174
	(0.014)	(0.017)	(0.011)	(0.019)
At least one parent born abroad	0.531	0.216	0.405	0.269
	(0.109)	(0.126)	(0.088)	(0.089)
ρ_1		0.148		0.054
		(0.012)		(0.024)
ρ_2		0.013		0.019
		(0.003)		(0.003)
Year dummies	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Constant	4.985	5.587	5.654	5.863
	(0.504)	(0.583)	(0.407)	(0.374)

Standard errors bootstrapped

Table D.17: Relationship between parental and ethnic capital and children education 1977-2010

	1977-2010	
	OLS	CF
Parental capital	0.247	0.193
	(0.006)	(0.004)
Ethnic capital	0.037	-0.042
	(0.020)	(0.026)
Ethnic capital X Female	0.129	0.145
	(0.022)	(0.034)
Female	-1.630	-1.828
	(0.251)	(0.416
Age	0.217	0.258
	(0.011)	(0.009)
Living in a city at the age of 16	0.305	0.388
	(0.040)	(0.043)
Living in a Southern	-0.126	-0.164
state at the age of 16	(0.071)	(0.066)
Number of siblings	-0.161	-0.184
	(0.009)	(0.009)
At least one parent born abroad	0.462	0.237
	(0.069)	(0.069)
ρ_1		0.096
		(0.002)
ρ_2		0.019
		(0.002)
Year dummies	Yes	Yes
Region dummies	Yes	Yes
Constant	6.214	6.796
	(0.006)	(0.499)

Standard errors bootstrapped