# The Occupational Selection of Emigrants

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**Abstract**

The current literature that investigates the selection of Mexican migrants to the United States focuses on selectivity in educational attainment and earnings. Notably absent from the literature is evidence on occupational selection, because it is unclear how to measure the skill content of Mexican occupations. However, any such research would yield important insights regarding the selection on labor-market skills that Mexicans carry with them to the United States. We use data from a representative Mexican worker survey—equivalent to the U.S. O*NET—to develop novel measures of cognitive and manual skills for migrants based on their pre-migration occupational history, and compare them to the skills of Mexicans who do not migrate. Using detailed longitudinal micro-level data from two Mexican labor surveys, the Mexican Migration Project, and the Mexican Family Life Survey, our analysis consistently shows that migrants have lower cognitive and higher manual skills than non-migrants. This finding is robust to controlling for age, gender, and educational attainment and also holds within broader occupational groups. Despite substantial changes in emigration rates over time, we also document that occupational selection is highly persistent. (*JEL* F22, O15, J61, J24)

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# I. Introduction

In 2012, 33.7 million migrants with Mexican origin resided in the United States, with 11.4 million who are Mexican-born (Gonzalez-Barrera and Lopez, 2013). Mexican migrants therefore constitute by far the largest foreign-born population in the United States; almost one-third of all foreigners are Mexican-born immigrants (Hanson and McIntosh, 2010). Knowing the skill structure of the migrant flow is important for informed labor-market and immigration policies on both sides of the border. For the United States, the skills that Mexican migrants carry with them determine how easily they can be integrated into the U.S. labor market and how they affect natives' earnings and employment. For Mexico, the characteristics of emigrants matter because of their implications for income and wealth inequality through, for instance, missing productive household members, remittances, and knowledge transfer back to Mexico.

Given its social and economic implications for both Mexico and the United States, it is not surprising that an abundant literature deals with the selectivity of Mexican migrants. However, this literature has used rather crude proxies for migrants' skills, focusing on education, predicted earnings based on a limited set of observables (such as age, gender, marital status, and education), and actual earnings.[1] Our paper is the first to look at the selection of migrants with regard to occupational skills, which are a more direct measure of the knowledge and capabilities relevant in the labor market than those previously investigated. For instance, although educational attainment tends to be a good predictor of labor-market success, it does not capture any skill developments after labor-market entry (e.g., due to on-the-job training). Moreover, skill categorizations based on educational attainment are very coarse (typically distinguishing only between low-skilled and high-skilled migrants) and implicitly assume that the education systems in Mexico and the United States are of comparable quality. Moreover, summary measures of skills, such as predicted or actual earnings, conceal the mechanism where the selection pattern comes from. In fact, previous studies have found a non-monotonic pattern regarding the probability of migration as a function of the wage residual, which an uni-dimensional skill measure cannot explain.

One major reason why occupational selection has not received any attention thus far is that there was no information about the occupational skills embodied in the jobs Mexican emigrants used to work in. However, new data from a large-scale Mexican worker survey—equivalent to the U.S. O*NET—allow for the first time to measure the skill content of Mexican occupations.[2] Based on these data, we characterize occupations by their skill content in terms of two dimensions, *cognitive* and *manual* skills.

We combine our occupational-skill measures with four micro-level datasets containing infor-

[1]Section II. provides a detailed literature overview.

[2]The survey has been conducted by the Instituto Nacional de Estradistica y Geografia (INEGI), and was published by its acronym SINCO (Sistema Nacional de Clasificación de Ocupaciones).

mation on the labor-market histories of Mexican workers. In particular, we use data from the National Survey of Occupation and Employment (ENOE), the Quarterly National Labor Survey (ENET), the Mexican Migration Project (MMP), and the Mexican Family Life Survey (MxFLS), all of which allow to identify migrants from Mexico to the United States. Importantly, all datasets also contain information on a worker's pre-migration occupation and a rich set of other socioeconomic characteristics that have previously been shown to be important for migrant selection. Due to the longitudinal dimension of the worker data, we can construct measures of cognitive and manual occupational skills based on several pre-migration occupations, accounting for the possibility that the last pre-migration occupation is endogenous to the migration decision.[3]

We first compare the occupational skills of migrants and non-migrants using non-parametric cumulative distribution functions. Consistently across datasets, we find that Mexican migrants to the United States are negatively selected on cognitive skills and are positively selected on manual skills. This selection pattern is similar in linear probability models that simultaneously include both skill measures and condition on educational attainment, gender, and age. In terms of magnitude, we find a 54% drop in the migration propensity for a one-standard-deviation increase in cognitive skills (e.g., corresponding to the cognitive-skill distance from a cook to a mechanical engineer). Similarly, the migration propensity increases by 17% for a one-standard-deviation increase in manual skills (e.g., from a police officer to an agricultural technician). These results also hold when we account for differences in the migration propensity and in occupational skills across broader occupational categories (up to the three-digit level). Thus, the observed selection pattern does not merely reflect that workers in certain occupational groups (e.g., agriculture) are more likely to migrate, but it also holds within narrowly defined occupations.

During the last 70 years, Mexico has experienced different phases of emigration waves (Hanson and McIntosh, 2010). While the Mexican-born population in the United States remained below the one-million mark during the *bracero* guest-worker program 1942–1964, the number of Mexican immigrants increased to about 9 million in 2000. More recently, the Mexican-born population in the United States has increased even more rapidly to a peak of 12 million in 2009/2010, and has slightly fallen afterwards. Exploiting that our worker data reach back until the 1950s, we can show that the described pattern of occupational selection remained highly persistent over the last decades. Thus, the skills of workers migrating from Mexico to the United States (relative to the skills of those left behind) are very similar in phases of sharp increases in net migration and in periods where net migration has plummeted.

Finally, our analysis of occupational skills also provides novel insights into the mechanisms behind migrant selection on other variables. For instance, the negative selection on educational attainment becomes considerable weaker and sometimes even turns out to be positive when we

[3]Using the MMP, we can even construct skill measures using the complete occupational history of workers.

condition on occupational skills. This suggests that the impact on the migration propensity of education materializes to a large extent through job choice. Once we hold constant the type of job workers have, people with better education are not less likely to migrate.

The remainder of the paper is structured as follows. Section II. provides an overview of the current literature of emigrant selection between Mexico and the United States. Section III. introduces the data. Section IV. presents our results on the occupational selection pattern of Mexican migrants, discusses their robustness, and investigates how they change over time. Section V. concludes.

## II. Related Literature

The selection of migrants from Mexico has been the subject of a series of papers. Table 1 summarizes the most recent selection papers in terms of the selection variable investigated, the direction of selection (negative, intermediate, positive, or no selection), the time period covered, and the data source. A highly influential paper by Chiquiar and Hanson (2005) uses the U.S. Census to identify Mexican migrants and computes predicted earnings for migrants and non-migrants from the Mexican Census, using the returns to observable factors (education, age, gender, and marriage status) in Mexico. Comparing predicted earnings of migrants and non-migrants, Chiquiar and Hanson (2005) find that Mexican migrants are drawn from the middle of the predicted earnings distribution in Mexico. They also find intermediate selection on educational attainment. Using the same approach of comparing Mexican migrants in the U.S. Census to Mexican non-migrants in the Mexican Census, Mishra (2007) and Feliciano (2008) even argue that Mexican migrants are better educated on average than those staying in Mexico. Orrenius and Zavodny (2005) use data from the MMP and confirm the finding from Chiquiar and Hanson (2005) of intermediate educational selection. Hence, all these earlier papers do not support the predictions of the basic Borjas model (Borjas, 1987) of negative migrant selection between Mexico and the United States.

Ibarraran and Lubotsky (2007) challenge these earlier findings using the U.S. and Mexican Census in 2000. They carefully compare migrants in the United States and return migrants in the Mexican Census to non-migrants in the Mexican Census and conclude that migrants are negatively selected. They explain their results by the fact that low-skilled and undocumented migrants are underreported in the U.S. Census. The result of intermediate selection obtained by Orrenius and Zavodny (2005) can potentially be explained by the fact that the MMP oversamples migrants in urban areas with a high migration propensity.[4] Using different Mexican data, McKenzie and Rapoport (2010) and Fernández-Huertas Moraga (2013) show that selection is likely to be negative in urban areas and areas with strong networks, both of which are characterized by large emigration propensities. Especially large networks decrease migration costs as low-skilled individuals

[4] See Section III. for details.

profit from low-cost information flows. On the other hand, positive selection prevails in rural areas and areas with weak networks. There, high migration costs prevent low-skilled individuals from migrating.

One lesson to be drawn from previous literature is that only longitudinal data which survey migrants before the move should be used. Fernández-Huertas Moraga (2011) draws on the ENET survey, which follows each sampled household for five quarters, to identify migrants to the United States. He finds that migrants are in fact negatively selected based on actual earnings and educational attainment. However, one disadvantage of this survey is that it does not keep track of entire households that migrate to the United States. This gap can be filled by the MxFLS, which follows migrants even in the United States (with a recontact rate of 90%). Using this dataset, Ambrosini and Peri (2012) and Kaestner and Malamud (2014) show that migrants are negatively selected based on actual earnings. Interestingly,Kaestner and Malamud (2014) find that migrants do not perform differently than non-migrants on Raven cognitive ability tests. Finally, Rendall and Parker (2014) combine different datasets to investigate educational selectivity over time. They consistently find that Mexican migrants are negatively selected.

To conclude, the sampling of migrants in different surveys is important to understand the results on migrant selection. Using the U.S. Census or U.S. sources to identify Mexican migrants should generally be avoided because low-skilled and undocumented migrants are most likely underreported (Hanson, 2006). The skill measure that is studied most is educational attainment, which is appealing because education is reported in almost every dataset and is typically fixed at labor-market entry. Selection on actual earnings show that migrants are persistently drawn from the lower part of the earnings distribution, but the main driver of this selection pattern is unclear. We complement the existing literature by revealing the selection of migrants with respect to the skills embodied in their pre-migration occupations, which is a more direct measure of the skills that Mexican emigrants carry with them than those previously used.

## III. Data

We draw on several datasets in this study. The primary innovation is the use of detailed information on the skill structure of Mexican occupations, equivalent to the U.S. O*NET, provided in the SINCO survey. We link these data to rich Mexican micro-level datasets that allow to identify migrants to the United States. For reasons of sample size and year coverage, we use the ENOE as our main data source. We check the sensitivity of our results by using data from ENOE's predecessor, the ENET, as well as from the MMP and the MxFLS. The following subsections describe the different data sources and discuss their advantages and disadvantages in the context of our study.

### A. *SINCO*

The main objective of the National Occupation Classification System (SINCO by its acronym in Spanish) is to reflect Mexico's true occupational structure and to be comparable with other international classification systems, in particular with those by the International Labour Organisation (ILO) and Mexico's main trading partners (USA and Canada). In response to this need, the SINCO was designed by the Sectoral Technical Committee of Labor Statistics and Social Provision[5] and has replaced previous official occupation systems in Mexico such as the Classification Mexicana de Ocupaciones (CMO). For example, the ENOE survey started using the SINCO after the second quarter of 2012 replacing the CMO.[6]

The SINCO is a representative worker survey, with 17,250 respondents in 443 occupations. The survey captures an exceptionally large set of aspects of job content, grouped into seven categories[7] with more than 100 questions in total. We reduce the dimensionality of the data by performing principal component analysis to construct our skill intensity measures. For cognitive intensity, we select variables on problem solving, proactivity, self-motivatedness, flexibility, independence, self-control, self-knowledge, creativity, active learning of workers and calculate the score corresponding to the first principal component (PC). For manual intensity, we use variables on strength, coordination and flexibility and balance and again define the measure by the score of the first PC for the relevant set of variables. The measures capture 54% and 48% of all variation, respectively, in the relevant subsets of the data. We aggregate the scores by using occupation averages on four-digit occupational classification level. The skill measures are normalized by mean and standard deviation in 2013, facilitating comparability over time.

Table 2 shows the top and bottom five occupations by their cognitive and manual skill content. Occupations like psychologists, secondary school teachers, college instructors, education program managers, and CEOs score high on cognitive skills, while sheet metal workers, harvesting laborers, carpenters, industrial mechanics, and butchers have high manual skills. In contrast, workers in the farming sector have lowest cognitive skills and telephone operators, sales representatives, university professors, accountants, and personnel administrators have lowest manual skills. Three observations emerge from this table: First, the PCA seems to yield a sensible classification of jobs along the two skill dimensions. Second, cognitive and manual skills are negatively correlated, but neither one is the mirror image of the other; the top-five cognitive skill occupations do not overlap with the bottom-five manual skill occupations or vice versa. Third, even within the top- and bottom-five occupations, there is some variation in the skills of the other skill dimension. For ex-

[5]This committee was composed of several agencies: Secretaria de Trabajo y Prevision Social (STPS), Instiuto Mexico de Seguridad Social (IMSS), and Instituto Nacional de Estadistica y Geografia (INEGI).

[6]See Appendix A for further details on the SINCO data.

[7]These categories comprise responsibility, knowledge, tools, abilities, social skills, traits, and physical skills.

ample, within the bottom-five manual skill occupations, we observe telephone operators who need only very little cognitive skills for their job and university professors who need very high cognitive skills.

### *B. Mexican Labor Force Survey (ENET/ENOE)*

We use the Mexican Quarterly Labor Force Survey as the main source of worker data in this paper. The data has been used extensively to study the selection of Mexican emigrants to the United States (see, e.g., Fernández-Huertas Moraga 2011, 2013; Rendall and Parker 2014). From 2000 to 2004, the Instituto Nacional de Estadística, Geografía e Informática (INEGI) conducted the Quarterly National Labor Survey (Encuesta Nacional de Empleo Trimestral – ENET). After 2004, the survey was replaced by the National Survey of Occupation and Employment (Encuesta Nacional de Ocupación y Empleo – ENOE). Due to the wider year coverage, we use ENOE in our main specifications.

The structure of the survey is comparable to the Current Population Survey (CPS) in the United States; it surveys households for five consecutive quarters and reports sociodemographic variables, such as age, gender, educational attainment, occupation, and earnings of (document and undocumented) U.S. emigrants and non-migrants. The panel structure of the survey allows the identification of emigrant characteristics shortly before the move. In all specifications using either ENOE or ENET, *US migrants* are defined as being between 16 and 65 years old, living in Mexico at quarter $t$, and have left for the United States at quarter $t+1$. *Mexicans*, on the other hand, live in Mexico at quarter $t$ and also at quarter $t+1$.

The main advantage of this survey (compared to the other surveys introduced below) is that it is nationally representative and reports occupational information at a very detailed level (four-digits). Detailed occupational coverage is especially important for us because we need this information to assign accurate occupational skills to each person. One main drawback of the survey is that it does not contain any information on migrants moving abroad with their whole household.

### *C. Mexican Migration Project (MMP)*

The MMP is a binational study based at the University of Guadalajara and the University of Pennsylvania. It surveys Mexican households in Mexican communities that are known for sending a large number of migrants to the United States. Areas sampled in the MMP are identified by surveying Mexican migrants in the United States and then surveying their home community in Mexico.[8] The survey started in 1982 and is conducted annually since 1987. At each interview, a retrospective life history of the household head is gathered. This includes, among others, migration experience,

[8]These Mexican communities likely have an above-average emigration propensity.

work history (including occupational information), and marriage behavior. The dataset also includes information on the spouse and the children of the household head. However, due to data quality, we restrict the analysis to the household head. Occupations in the MMP are provided at the three-digit level.

Since one main aim of the MMP is to gather accurate data on documented and undocumented Mexican migration to the United States, respondents answer detailed questions on their migration episodes. In the analyses using MMP data, we define *US migrants* as being between 16 and 65 years old, living in Mexico at year $t$, and have left for the United States the year after. *Mexicans* are required to live in Mexico in years $t$ and $t+1$.[9]

A unique feature of the survey is that it contains occupational information over a worker's whole career, allowing us to test the robustness of our results with respect to the occupation that best proxies a worker's skills (e.g., first occupation, last pre-migration occupation, rolling average over all pre-migration occupations etc.). Since it covers retrospective life histories, the MMP also includes information whether migrants to the United States returned to Mexico and whether they leave again for the United States.[10] This allows us to investigate whether the pattern of occupational selection is different for people with several Mexico-U.S.-migration episodes. Moreover, the MMP is representative for immigrant-sending communities. Its main disadvantage is that it provides a selected sample of mainly urban communities with relatively high emigration propensities.

### *D. Mexican Family Life Survey (MxFLS)*

The MxFLS is a nationally representative household panel that follows individuals and households over time. The first round took place in 2002 and surveyed about 8,000 households in Mexico. Each member of the household was surveyed. The second and third round took place in 2005 and 2009, respectively. A unique feature of the survey is that respondents are followed even to the United States, with recontact rates for migrants and non-migrants as high as 90%. Thus, sample attrition is unlikely to be a problem in this survey.

The main advantage of the survey is that it is representative for the Mexican population. The survey also covers entire households that emigrated to the United States. Thus, it deals with many sample selection problems that other surveys suffer from. Since the survey does not rely on retrospective information, the problem of measurement error is reduced. Main disadvantages of the survey are the relatively small sample size of the migrant population and that information on occupations is provided only at the two-digit level.[11]

[9]The MMP data reach back until 1889. However, since we observe very little migration in the first half of the 20th century, we drop years before 1950.

[10]Due to its limited time coverage, such information cannot be obtained from the Mexican Labor Force Survey.

[11]Due to the coarse occupational information in the MxFLS, our measures of cognitive and manual occupational skills likely yield considerable measurement error. The exposition in the paper thus focuses on the Mexican Labor

## IV. Results

How do the occupational skills of migrants to the United States compare to workers staying in Mexico? We approach this question in several ways. First, we provide descriptive statistics on the patterns of migrant occupational selection and compare the distributions of occupational skills of migrants and non-migrants (Section A.). Second, we perform multivariate regressions controlling for basic sociodemographic characteristics, which may confound the results in the descriptive exercise (Section B.). We also test the robustness of the selection pattern to adding further controls and assess its consistency across datasets. Third, we study the long-run evolution of emigrant occupational selection over periods of high and low net migration to the United States (Section C.).

### *A. Descriptive Evidence on Emigrant Occupational Selection*

Table 3 shows the results of the descriptive analysis across the four worker-level datasets described above. The table reports the migration propensity at different points of the skill distribution. To make effect sizes comparable, we scale the migrantion propensity by the mean emigration rate in each survey. In our main dataset (ENOE), we find that emigrants are 72.2% more likely to emigrate when they belong to the third (bottom) tertile of the cognitive skill distribution compared to having mean cognitive skills. Conversely, compared to the mean, emigrants are 53.4% less likely to belong to the first (top) tertile of the cognitive skills distribution. We find the opposite pattern for manual skills. Emigrants are 52.3% less likely to come from the third tertile of the manual skill distribution and 49.6% more likely to come from the first tertile. This indicates that Mexican emigrants to the United States are negatively selected compared to non-migrants in terms of cognitive skills and positively selected in terms of manual skills. Strikingly, the selection is very similar across the other three datasets, both in term of the general pattern of selection and the differences in migration propensities between different points in the skill distribution.[12] For comparison, we also look at the educational selection of emigrants. Here, we can confirm previous findings by showing that Mexican emigrants are mostly coming from the middle of the educational distribution, suggesting intermediate educational selection.

These results are confirmed by looking at the cumulative distribution functions (CDF's) of cognitive and manual skills by migrant status. Figure 1 plots the CDFs for the ENOE data. We find that the CDF of cognitive skills for migrants is to the left of the CDF for non-migrants. This indicates that migrants are negatively selected on cognitive skills along the entire skill distribution. For manual skills, we find that the CDF of migrants is to the right of the CDF of non-migrants, indicating positive selection. Kolmogorov-Smirnov tests on stochastic dominance confirm that the

Force Survey and the MMP.

[12]Differences are somewhat less pronounced along the cognitive skills distribution in the MMP and MxFLS as compared to ENOE and ENET, but are still highly statistically significant.

CDF's are significantly different from each other throughout. This pattern of occupational selection is similar in the MMP and ENET (Figure B1).

### *B. Multivariate Analysis of Emigrant Occupational Selection*

The analysis above shows that occupational skills are a strong predictor of the emigration propensity. In Table 4, we estimate linear probability models to predict the migration propensity to the United States using the ENOE data. In Column 1, we model the migration propensity when conditioning only on education, gender, and age.[13] We find that education is negatively related to the migration propensity and that migrants are more likely to be female and younger than non-migrants. Columns 2 and 3 introduce our occupational skill measures. Conditional on sociodemographic variables, we still find that workers with higher cognitive skills are less likely to migrate and that workers with higher manual skills are more likely to migrate. Including both skill measures simultaneously does not change the picture (Column 4).

From Table 2 we have seen that there are occupations with similar levels of cognitive skills, but with very different levels of manual skills (and vice versa). To trace out these effects, we add the interaction between cognitive and manual skills in Column 5, which turns out to be negative but leaves the selection pattern unaffected. Furthermore, these results are not just driven by differences in the job content between coarse occupational categories, say, between agriculture and services. In fact, we can control for occupation fixed effects even at the three-digit level and observe a qualitatively similar selection pattern (Column 6).[14]

We now use the coefficients in Column 5 in Table 4 to judge the economic significance of the selection on cognitive and manual skills. An increase in cognitive skills by one standard deviation, ceteris paribus, is associated with a drop in the propensity to migrate by 54%. This is equivalent to comparing the migration propensities of a cook (at the mean of the cognitive skill distribution) to a mechanical engineer (+1 standard deviation in cognitive skills). Similarly, increasing manual skills by one standard deviation, we observe an increase in the propensity to migrate by 17%. This is equivalent to comparing the migration propensities of a police officer (at the mean of the manual skill distribution) to an agricultural technician (+1 standard deviation in manual skills).

Containing information on migrants' entire life history, the MMP data provide the opportunity to check whether the limited time coverage in ENOE can potentially confound the results. Table 5 reports the results for the MMP-based analysis. Columns 1–5 replicate the baseline models from Table 4, but use information on workers' full occupational history to construct the occupational skill measures. Corroborating the descriptive results in Table 3, the selection pattern is remarkably

[13] All models include further include quarter-by-year fixed effects which control for temporal migration shocks.

[14] Table B1 replicates the analysis with ENET, ENOE's predecessor. Results are very similar, in terms of both coefficient magnitude and statistical significance. This is a first indication that the observed pattern of occupational selection is very stable over time. See Section C. for a more detailed analysis.

robust across datasets. In Column 6, we only keep spells of migrants before their first move to the United States, that is, we drop observations of Mexican emigrants who return to their home country. The findings indicate that not having information on previous migration episodes is unlikely to bias results with the ENOE data. In Column 7, our calculation of cognitive and manual occupational skills is based only on the pre-migration occupation instead of using the job content of all occupations held since labor-market entry. Results hardly change compared to the baseline. Column 8 additionally controls for a full set of state-of-birth fixed effects to capture different migration trends across Mexican states that are potentially correlated with the occupational structure in these states.[15] Results indicate that any differences in cross-state migration (e.g., due to regional Mexico–U.S. migration networks or geographic location) cannot explain the observed pattern of occupational selection.[16]

Finally, accounting for occupational skills also provides novel insights into the mechanisms behind the negative (to intermediate) educational selection found in previous studies. Both ENOE and MMP also indicate negative educational selection prima facie. However, once we condition the estimates on occupational skills, this negative educational selection becomes considerable weaker and is even positive in the ENOE analysis. This suggests that the impact on the migration propensity of educational attainment materializes to a large extent through job choice. Put differently, once holding constant the type of job workers have, people with better education are not less likely to migrate.[17]

### *C. Emigrant Occupational Selection over Time*

In the last 15 years, Mexico has experienced very different emigration waves. The Mexican-born population in the United States has increased rapidly between 2000 and 2009/2010, from about 9 million at the beginning of the century to more than 12 million one decade later. Recently, however, net migration from Mexico to the United States was negative, so the Mexican-born population has fallen below 12 million in 2013. In light of these different emigration waves, the question arises whether the occupational skills of Mexican emigrants systematically change with the scale of migration. Thus, Figure 2a plots the migration propensities for a one-standard-deviation increase in cognitive (blue line) and manual (green line) occupational skills, respectively.[18] For comparison, the right axis shows the Mexican-born population in the United States. We observe that, remarkably, Mexican emigration has always been positively selected on manual skills and negatively

[15]We prefer to control for birth state effects instead of pre-migration state effects (which are available in the ENOE) because the latter may be endogenous to the migration decision.

[16]A couple of further results are noteworthy. The pattern of occupational selection appears to be driven by men and is similar in rural and urban areas. It is also robust to accounting for selection on earnings.

[17]Although the coefficient on schooling has a negative sign in the MMP analysis throughout specifications, it dwarfs once we account for occupational skills and is typically only marginally significant.

[18]Estimates are based on the model in Column 5 in Table 4.

selected on cognitive skills over the entire period between 2000 and 2013.

While 2000–2013 was a period of high emigration in general, one might wonder how the selection pattern looks like in times of low emigration. Figure 2b provides an answer to this question. Even though emigration rates in the 1950s, 1960s, and most of the 1970s were very low, the occupational selection pattern of Mexican emigrants shows a considerable persistence. This is also true for the period from 1970 to 2000, when the United States experienced an increase in the Mexican-born population from almost zero to around 9 million.

## V. Conclusions

This is the first paper that provides a detailed picture of the occupational selection of emigrants. We construct novel measures of cognitive and manual skills of workers based on their pre-migration occupational histories, and apply them to Mexican emigrants to the United States as one of the world's largest between-country migration relationships. We find that Mexican emigrants are negatively selected on cognitive skills and are positively selected on manual skills. This selection pattern is remarkably stable across datasets and over time. It is also robust to accounting for many of the selection mechanisms studied in previous papers, that is, selection on education, age, and actual earnings.

Our analysis provides an important building block toward better understanding the sources and mechanisms of emigrant selection. We show that occupational skills play an important role in emigrant selection and could therefore better inform politicians on both sides of the border about who leaves and who comes. Moreover, occupational selection also informs researchers how to interpret their findings with regard to labor-market effects of Mexicans in the United States. For instance, we find that much of the educational selection of Mexican emigrants can be explained by their choice of jobs. In fact, once we hold constant the type of job workers have, Mexicans with better education are not less likely to migrate.

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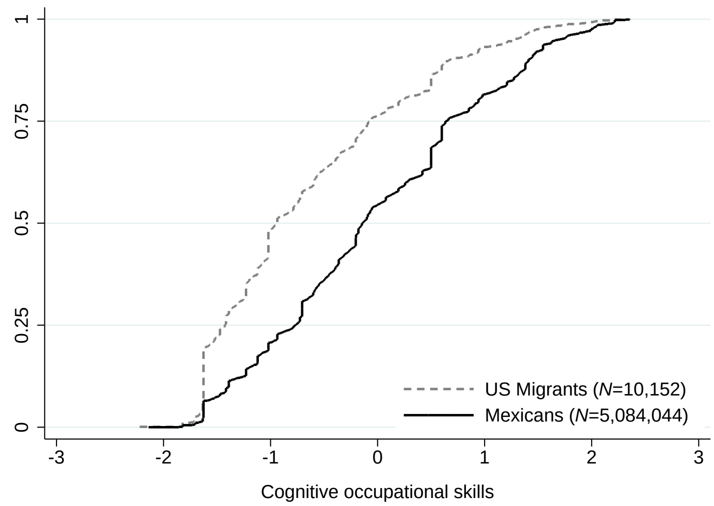
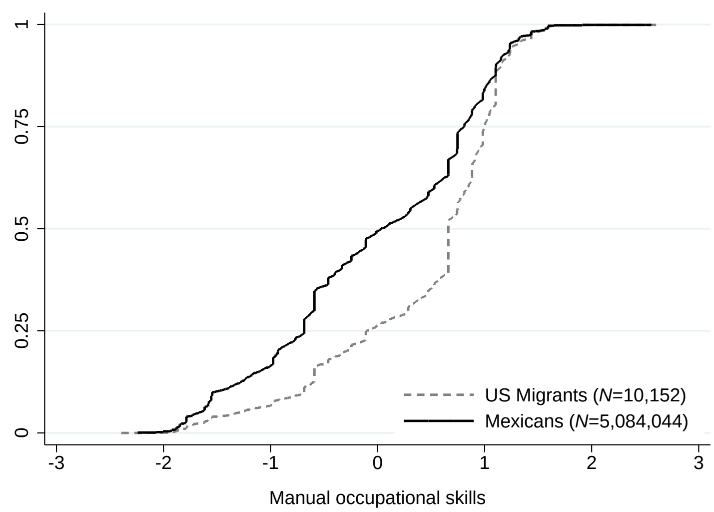
## Figures and Tables

**Figure 1:** CDFs of Emigrant Selection on Occupational Skills

**(a)** Cognitive Skills



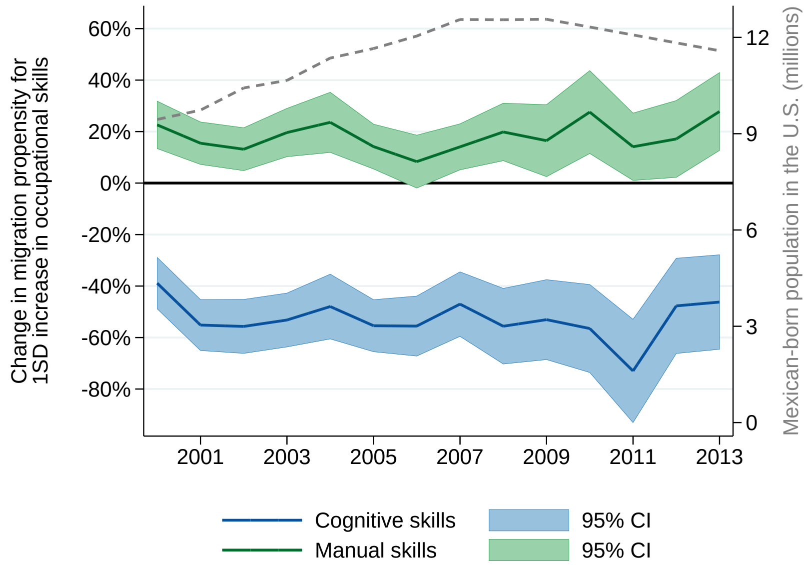

**(b)** Manual Skills



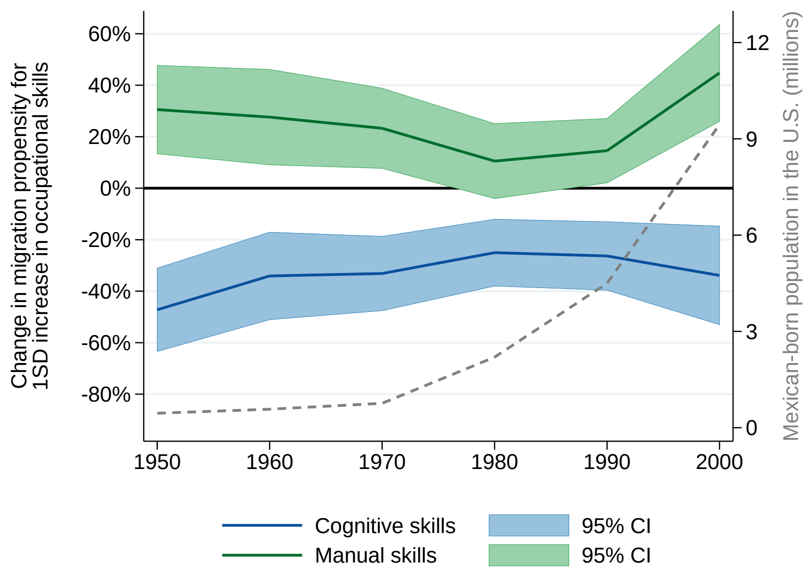

*Notes*: The figures show cumulative distribution functions of cognitive occupational skills (upper panel) and manual occupational skills (lower panel) by migration status. Kolmogorov-Smirnov test on stochastic dominance indicate that differences are significant at the 1% level. *Data source:* ENOE.

**Figure 2:** Emigrant Selection over Time

**(a)** Recent Pattern: 2000–2013




**(b)** Long-Run Perspective: 1950–2000




*Notes*: The figures show the change in emigration propensity for a one-standard-deviation increase in occupational skills. *Data sources:* ENET/ENOE (Figure 2a) and MMP (Figure 2b).

**Table 1:** Literature on the Selection of Mexican Migrants to the United States

| Paper | Skill Measure | Selection | Time Period | Data Source |
|---|---|---|---|---|
| Chiquiar and Hanson (2005) | predicted earnings | $\wedge$ | 1990, 2000 | U.S. and Mexican Census (1990, 2000) |
| | education | $\wedge$ | | |
| Orrenius and Zavodny (2005) | education | $\wedge$ | 1982-1997 | MMP (1982, 1987 - 1997) |
| Ibarraran and Lubotsky (2007) | education | – | 2000 | Mexican Census (2000) |
| Mishra (2007) | education | + | 1970-2000 | U.S. and Mexican Census (1970, 1990, 2000) |
| Feliciano (2008) | education | + | 1960-2000 | U.S. and Mexican Census (1960, 1970, 1990, 2000) |
| McKenzie and Rapoport (2010) | education | – (strong networks) / + (weak networks) | 1997 | ENADID (1997) |
| Fernández-Huertas Moraga (2011) | actual earnings | – | 2000-2004 | ENET (2000-2004) |
| | education | – (men) / + (women) | | |
| Ambrosini and Peri (2012) | actual earnings | – | 2002-2005 | MXFLS (2002, 2005) |
| | education | – | | |
| Fernández-Huertas Moraga (2013) | actual earnings | – (urban) / + (rural) | 2000-2004 | ENET (2000-2004) |
| | education | – (urban) / + (rural) | | |
| Kaestner and Malamud (2014) | actual earnings | – (men) | 2002-2005 | MXFLS (2002, 2005) |
| | education | $\wedge$ | | |
| | cognitive ability | 0 | | |
| Rendall and Parker (2014) | education | – | 1987-2010 | ENADID (1992, 1997, 2006, 2009), ENE (2002), ENOE (2006-2010), MXFLS (2002, 2005) |

*Notes:* The table shows related papers that look at migrant selection between Mexico and the United States. *Selection:* "–" indicates that the study finds negative selection, that is, non-migrants are more skilled than migrants. "+" indicates that the study finds positive selection, that is, migrants are more skilled than non-migrants. "$\wedge$" indicates that the study finds intermediate (to positive) selection, that is, migrants are drawn from the middle of the skill distribution. "0" indicates that the study finds no selection. *Data Source:* MMP: Mexican Migration Project; MXFLS: Mexican Family Life Survey; ENADID (Encuesta Nacional de la Dinámica Demográfica): National Survey of Demographic Dynamics; ENE (Encuesta Nacional de Empleo): National Employment Survey; ENOE (Encuesta Nacional de Ocupación y Empleo): National Survey of Occupation and Employment; ENET (Encuesta Nacional de Empleo Trimestral): Quarterly National Labor Survey.

**Table 2:** Skill Content of Mexican Occupations

| **Top 5 Occupations** | | | | | |
|---|---|---|---|---|---|
| **Cognitive Occupational Skills** | | | **Manual Occupational Skills** | | |
| Occupation | Cognitive Score | Manual Score | Occupation | Manual Score | Cognitive Score |
| Psychologists | 2.21 | -1.33 | Sheet Metal Workers | 1.59 | -0.16 |
| Secondary School Teachers | 2.11 | -0.73 | Harvesting Laborers | 1.58 | -0.91 |
| College Instructors | 2.10 | -1.12 | Carpenters | 1.53 | -0.11 |
| Education Prog. Managers | 2.02 | -1.04 | Industrial Mechanics | 1.53 | -0.13 |
| CEOs | 1.96 | -0.28 | Butchers | 1.50 | -0.39 |
| **Bottom 5 Occupations** | | | | | |
| **Cognitive Occupational Skills** | | | **Manual Occupational Skills** | | |
| Occupation | Cognitive Score | Manual Score | Occupation | Manual Score | Cognitive Score |
| Stock Farmers | -1.76 | 0.28 | Telephone Operators | -2.06 | -0.48 |
| Farmers, agricultural crops | -1.65 | 1.19 | Sales Representatives | -1.93 | 0.23 |
| Farmers, vegetables/greens | -1.58 | 0.85 | University Professors | -1.85 | 1.92 |
| Farmers, corn/beans | -1.57 | 0.64 | Accountants | -1.80 | 1.34 |
| Farmers, fruit crops | -1.43 | 0.88 | Personnel Administrators | -1.77 | 1.45 |

*Notes:* Ranking of occupations is based on empirical distribution in ENOE (2005–2014). Skill measures are normalized by mean and SD in 2013. *Data source:* SINCO.

**Table 3:** Descriptive Statistics on Migrant Selection

| | ENOE | | ENET | | MMP | | MXFLS | |
|---|---|---|---|---|---|---|---|---|
| | 2005–2014 | | 2000–2004 | | 1950–2011 | | 2002–2006 | |
| | Migration Propensity | Diff. from Reference Category | Migration Propensity | Diff. from Reference Category | Migration Propensity | Diff. from Reference Category | Migration Propensity | Diff. from Reference Category |
| **Cognitive occupational skills** | | | | | | | | |
| 3rd (bottom) tertile | 1.722 | | 1.639 | | 1.327 | | 1.387 | |
| 2nd tertile | 0.688 | -1.034*** | 0.737 | -0.902*** | 1.089 | -0.238*** | 0.945 | -0.442*** |
| 1th (top) tertile | 0.466 | -1.256*** | 0.367 | -1.271*** | 0.664 | -0.663*** | 0.671 | -0.716*** |
| **Manual occupational skills** | | | | | | | | |
| 3rd (bottom) tertile | 0.477 | | 0.397 | | 0.575 | | 0.641 | |
| 2nd tertile | 1.056 | 0.579*** | 0.874 | 0.477*** | 1.242 | 0.667*** | 0.859 | 0.218** |
| 1th (top) tertile | 1.496 | 1.019*** | 1.575 | 1.178*** | 1.374 | 0.799*** | 1.587 | 0.946*** |
| **For comparison: Education** | | | | | | | | |
| 0–3 years of schooling | 0.924 | | 0.886 | | 0.939 | | 0.747 | |
| 4–6 years of schooling | 1.298 | 0.374*** | 1.476 | 0.590*** | 1.118 | 0.179*** | 1.139 | 0.392** |
| 7–9 years of schooling | 1.233 | 0.309*** | 1.187 | 0.301*** | 1.243 | 0.304*** | 1.193 | 0.446*** |
| 10–12 years of schooling | 0.827 | -0.097** | 0.814 | -0.072*** | 0.881 | -0.058 | 1.161 | 0.415*** |
| More than 12 years of schooling | 0.555 | -0.369*** | 0.314 | -0.572*** | 0.495 | -0.444*** | 0.368 | -0.378** |
| Total observations | 5,094,196 | | 3,765,142 | | 525,596 | | 28,193 | |
| *U.S. migrants* | 10,152 | | 12,299 | | 10,704 | | 566 | |

*Notes:* Samples consist of Mexican males and females aged 16 to 65. To account for different migrant shares across datasets, we scale migrant status by migrant share to obtain *Migration Propensity*. Cognitive and manual skills incorporate full observed worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations. Skill measures are normalized by mean and SD from last available full year in the respective dataset (ENET uses ENOE standardization). Statistical difference from the reference category is tested with two-sided $t$-test. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table 4:** Migrant Occupational Selection: Baseline Results

| Dependent Variable: Migration Propensity to the U.S. | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cognitive skills | | –0.525*** | | –0.486*** | –0.540*** | –0.306*** |
| | | (0.023) | | (0.026) | (0.027) | (0.048) |
| Manual skills | | | 0.303*** | 0.076*** | 0.172*** | 0.113** |
| | | | (0.019) | (0.021) | (0.022) | (0.045) |
| Cognitive $\times$ manual skills | | | | | –0.459*** | –0.270*** |
| | | | | | (0.024) | (0.041) |
| Education | –0.060*** | 0.016*** | –0.029*** | 0.018*** | 0.010** | 0.020*** |
| | (0.004) | (0.005) | (0.004) | (0.005) | (0.005) | (0.005) |
| Female | –1.129*** | –0.916*** | –1.001*** | –0.900*** | –0.851*** | –0.732*** |
| | (0.031) | (0.028) | (0.029) | (0.028) | (0.027) | (0.032) |
| Age | –0.040*** | –0.035*** | –0.038*** | –0.035*** | –0.035*** | –0.035*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Quarter-by-year fixed effects | X | X | X | X | X | X |
| Occupation fixed effects (156) | | | | | | X |
| $R^2$ | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 |
| Observations | 5,094,196 | 5,094,196 | 5,094,196 | 5,094,196 | 5,094,196 | 5,094,196 |

*Notes:* Sample consists of Mexican males and females aged 16 to 65. Dependent variable is migrant status scaled by quarterly migrant share. Cognitive and manual skills incorporate full observed worker history; they are defined as (unweighted) averages of skill content of current and all previous (max. four) occupations. Skill measures are normalized by mean and SD from 2013. Occupation fixed effects are at the three-digit level and refer to last observed occupation. All regressions are weighted by sampling weights. Standard errors (in parentheses) are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* ENOE, Q1-2005–Q2-2014.

**Table 5:** Migrant Occupational Selection: MMP

| Dependent Variable: Migration Propensity to the U.S. | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Baseline | | | No return | Last occ. | State FE |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Cognitive skills | | –0.296*** | | –0.251*** | –0.220*** | –0.184*** | –0.225*** | –0.272*** |
| | | (0.022) | | (0.030) | (0.029) | (0.034) | (0.030) | (0.030) |
| Manual skills | | | 0.263*** | 0.067** | 0.113*** | 0.099*** | 0.098*** | 0.104*** |
| | | | (0.022) | (0.029) | (0.030) | (0.037) | (0.029) | (0.031) |
| Cognitive skills × manual skills | | | | | –0.099*** | –0.080*** | –0.169*** | –0.083*** |
| | | | | | (0.015) | (0.017) | (0.018) | (0.016) |
| Education | –0.058*** | –0.011* | –0.028*** | –0.011* | –0.016** | –0.015** | –0.021*** | –0.001 |
| | (0.005) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.006) | (0.007) |
| Female | –0.657*** | –0.430*** | –0.470*** | –0.417*** | –0.392*** | –0.273*** | –0.357*** | –0.345*** |
| | (0.042) | (0.044) | (0.044) | (0.045) | (0.045) | (0.053) | (0.052) | (0.047) |
| Age | –0.046*** | –0.043*** | –0.043*** | –0.042*** | –0.043*** | –0.061*** | –0.043*** | –0.047*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Birth state fixed effects | | | | | | | | X |
| Year fixed effects | X | X | X | X | X | X | X | X |
| $R^2$ | 0.006 | 0.008 | 0.007 | 0.008 | 0.008 | 0.007 | 0.008 | 0.015 |
| Observations | 525,596 | 525,596 | 525,596 | 525,596 | 525,596 | 437,703 | 450,208 | 525,119 |

*Notes:* Sample includes Mexican males and females aged 16 to 65 (in Column 6, we drop all observations after the first move to the United States, i.e., estimation is without return migrants). Dependent variable is migrant status scaled by annual migrant share. Cognitive and manual skills incorporate full observed worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations. Skill measures are normalized by mean and SD from 2011 (last available year in MMP). In Column 7, we consider only the last pre-migration occupation to calculate occupational skill measures; people without occupational information immediately before migration are dropped. Robust standard errors, shown in parentheses, are clustered at the individual level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data Source:* MMP.

## Appendix A: Details on SINCO

The SINCO's is formed by occupations, each of which is understood as "the set of tasks and duties performed or expected to be performed by an individual, for an employer or for himself/herself." In order to group them, it is necessary to identify which of them share common characteristics and which do not, and this allows one to create a set of groups and, consequently, to start to bring order to a universe that otherwise would be chaotic. The resulting groups are what is called "occupation" that is, "a set of jobs whose main tasks and duties are characterized by a high degree of similarity", regardless of where the job is performed and the relationships established with other actors in the labor market. As with jobs, occupations are grouped into larger units and how they are grouped is the result of their being organized according to the nature of the work done. The nature of the work done is understood as the contextual and essential features of the occupations, such as purpose, functions, types of procedures, expertise, position in the production process, variability of activities, autonomy, etc.

Another significant element in the formation of the groups is the concept of competence, understood as "the ability to perform the tasks and duties of a particular job." Generally speaking, competence involves the ability to apply a set of attributes to working in different contexts and under different conditions, in other words, knowledge combined with the ability to develop certain skills such as: the ability to communicate with colleagues and customers; the ability to negotiate and exchange information; planning and working as a team; reading, writing and mathematical skills; the ability to operate machinery or specialized equipment, among others. This concept is operationalized using two criteria: skills level and specialization skills. The first criterion is mainly used to establish the highest aggregation level in the classification (division) defined according to the complexity and diversity of the tasks and duties performed within an occupation.

This complexity is basically measured by the skills levels already established by the International Standard Classification of Occupations (ISCO-08), so each level is determined by certain demands, tasks and requirements that are typical of the occupations and that are established for a repeat analysis of the nature of the work and the level of training, whether formal or informal. In other words, at the operational level, the skill level is measured through one or more of the following elements, in which case the so-called "nature of the job" cannot be disregarded:

- The nature of the work done, where work means the carrying out of an economic activity, whether independently or in a secondary way.
- The level of formal education that is expressed as four values (1 to 4), corresponding to a similar number of skills levels as established under the International Standard Classification of Education (ISCED-97) that are needed to effectively carry out the required tasks and duties.

These requirements for training and formal education, are only one component of the measurement of skill levels, and so in the event that occupations have similar tasks, duties or content but different "skill level" requirements, priority is given to the labor content, because what is being classified is the job and not the qualifications or level of education.

Therefore, the following definitions of the four skill levels serve to clarify the boundaries between them, as well as to deal with cases where formal education requirements are not the most suitable method for measuring the skills level of a particular occupation.

Occupations under skills level 1 require the performance of simple, routine physical or manual tasks. They may also require strength and / or physical stamina, and / or require the use of hand tools such as shovels, or simple electrical equipment, such as a vacuum cleaner. Some occupations at this level may require basic literacy and numeracy; in the latter case, these skills should not represent a significant part of the occupation. Included in this skills level are tasks such as cleaning, excavation, lifting or manual transportation of materials; selection, storage or manual product assembly; operation of non-motorized vehicles as well as picking fruit and vegetables.

Occupations under skills level 2 require the performance of tasks such as operating machinery and electronic equipment, driving vehicles and handling, organization and storage of information. It is essential to know how to read information such as safety instructions, draft written reports on completed jobs and do simple arithmetic calculations accurately, and so for many occupations at this level a relatively advanced level of literacy and numeracy is needed, as well as good interpersonal communication skills for much of the work being done. In some cases, experience and workplace training may replace formal education.

Occupations under skills level 3 require the performance of complex technical and practical functions based on concrete knowledge in a specialized area. They require an intermediate level of literacy and numeracy, as well as strong interpersonal communication skills. These skills may include the ability to understand written material of a technical nature, prepare documented reports and communicate verbally in difficult situations. In some cases, broad work experience and extensive workplace training can be substituted for formal education. Also included under this skills level are occupations involving supervision of personnel or responsibilities in the area of health or public safety.

The occupations under skills level 4 require the performance of functions that involve decision making and complex problem solving based on a broad theoretical and practical knowledge in a particular area. The functions typically include analysis and research to develop human knowledge in a particular field, diagnosis and treatment of disease, imparting knowledge to others, design of structures or machinery and of construction and production processes. Generally they require a higher level of literacy and numeracy, sometimes a very high level, as well as excellent interpersonal communication skills. These skills often include the ability to understand specialized written material and communicate complex ideas from media such as books, reports and oral presentations.

In some cases, formal education can be replaced by experience and workplace training. In many cases, relevant formal qualifications are essential for carrying out the job. The second criterion is specialization skills, which refer to specific features of the occupation such as the type of knowledge, skills and competences that come into play in performing the occupation, equipment or machinery used, materials utilized, the nature of the goods and services produced, and the setting in which work takes place. This criterion makes it possible to differentiate the occupations at the more detailed levels of the classification (from main to unitary group). This means occupations with similar tasks can be separated based on the knowledge required, tools used and material produced. They can also be linked together and therefore reflect the industry of the establishment where the work is performed.

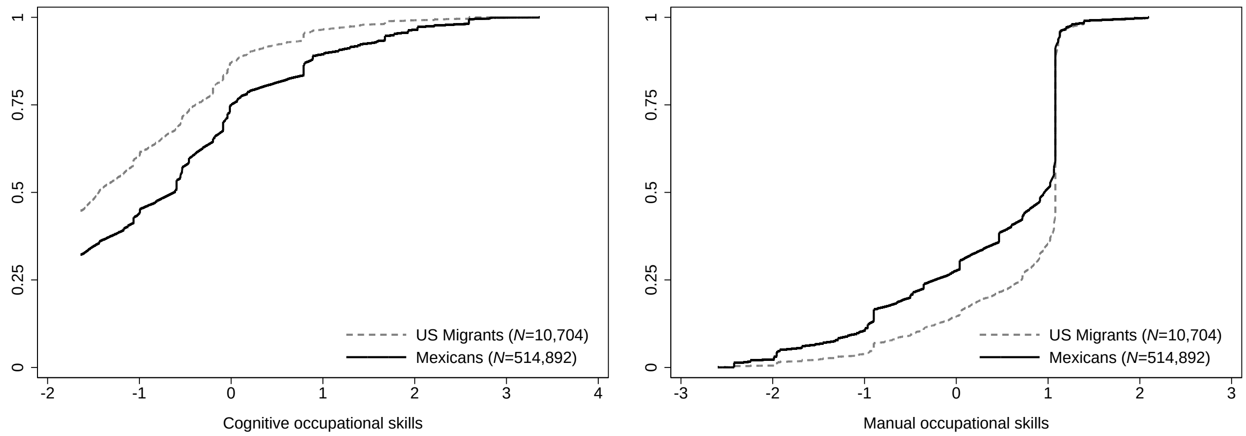
The structure of the classification was organized into four clustering levels, from the general to the specific, to facilitate the classification and identification of each occupation to determine the degree of flexibility and versatility shown with regard to the uses of this classification and the needs it is aiming to satisfy. Each clustering level has a code or key that makes it possible to collect, incorporate, process and present statistical results for each hierarchical or clustering level. Organizing the division into levels with a unique key for each of them, allows for a classification where all the elements of interest (occupations) are taken into account, both individually and grouped with those with whom they share certain common features. This in turn ensures that information on the Mexican job market is generated: from the most clustered level (main occupational categories or divisions) to the most detailed, i.e., occupations.

In the SINCO, the broadest level is the division, followed by the main group, then the subgroup and finally the unitary group. As in the ISCO-08, in the SINCO the main criterion for creating the occupational classification is the skills level, and therefore nine occupational categories are identified, making up the first level or division, which is identified by a digit that is the whole key.

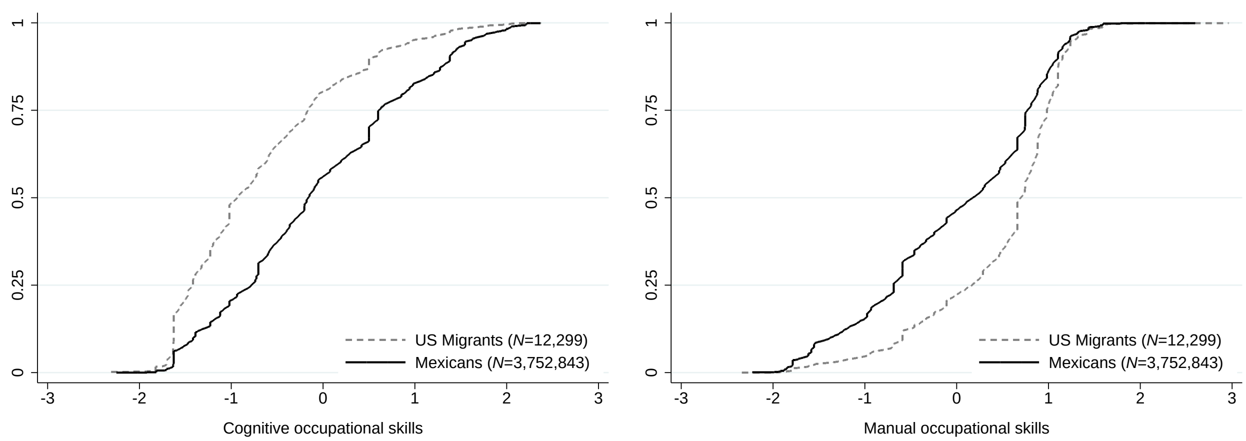
## Appendix B: Further Results

**Figure B1:** CDFs of Emigrant Selection on Occupational Skills: Other Datasets

**(a)** MMP




**(b)** ENET




*Notes*: The figures show cumulative distribution functions of cognitive and manual occupational skills by migration status. Differences in occupational selection between migrants and non-migrants are significant at the 1% level (Kolmogorov-Smirnov tests). *Data sources:* MMP (Figure B1a) and ENET (Figure B1b).

**Table B1:** Migrant Occupational Selection: Results from ENET

| Dependent variable: Migration Propensity to the U.S. | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cognitive skills | | –0.511*** | | –0.475*** | –0.500*** | –0.300*** |
| | | (0.020) | | (0.024) | (0.025) | (0.045) |
| Manual skills | | | 0.348*** | 0.061*** | 0.160*** | 0.122*** |
| | | | (0.017) | (0.020) | (0.021) | (0.042) |
| Cognitive skills × manual skills | | | | | –0.426*** | –0.287*** |
| | | | | | (0.021) | (0.037) |
| Education | –0.054*** | –0.007** | –0.032*** | –0.007** | –0.012*** | –0.010*** |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) |
| Female | –1.278*** | –0.979*** | –1.098*** | –0.968*** | –0.967*** | –0.837*** |
| | (0.031) | (0.028) | (0.030) | (0.028) | (0.028) | (0.033) |
| Age | –0.041*** | –0.039*** | –0.039*** | –0.039*** | –0.039*** | –0.045*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Quarter-by-year fixed effects | X | X | X | X | X | X |
| Occupation fixed effects (156) | | | | | | X |
| $R^2$ | 0.003 | 0.003 | 0.003 | 0.003 | 0.004 | 0.005 |
| Observations | 3,765,142 | 3,765,142 | 3,765,142 | 3,765,142 | 3,765,142 | 3,356,021 |

*Notes:* Sample consists of Mexican males and females aged 16 to 65. Dependent variable is migrant status scaled by quarterly migrant share. Cognitive and manual skills incorporate full observed worker history; they are defined as (unweighted) averages of skill content of current and all previous (max. four) occupations. Skill measures are normalized by mean and SD from 2013. Occupation fixed effects are at the three-digit level and refer to last observed occupation. All regressions are weighted by sampling weights. Standard errors (in parentheses) are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data source:* ENET, Q2-2000–Q3-2004.