International Emigrant Selection on Occupational Skills

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Abstract

We present the first evidence on the role of occupational choices and acquired skills for migrant selection. Combining novel data from a representative Mexican task survey with rich individual-level worker data, we find that Mexican migrants to the United States have higher manual skills and lower cognitive skills than non-migrants. Results hold within narrowly defined region-industry-occupation cells and for all education levels. Consistent with a Roy/Borjas-type selection model, differential returns to occupational skills between the United States and Mexico explain the selection pattern. Occupational skills are more important to capture the economic motives for migration than previously used worker characteristics. (*JEL* F22, O15, J61, J24)

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I Introduction

The worldwide stock of international migrants amounts to 258 million people (equivalent to 3.4% of the world population), having increased by almost 70% over the last 25 years (United Nations, 2017). International migration is often directed toward developed countries. Between 1990 and 2017, the population share of international migrants in developed countries has increased from 7.2% to 11.6%. Moreover, a substantial share of these moves is work related.[1] Because international migrants make up a sizeable fraction of the labor force in many countries, knowing the skill structure of the migrant flow—and the factors determining it—yields important information for labor-market and immigration policies. For the receiving country, the skills of immigrants determine how easily they can be integrated into the labor force and how they will affect natives' earnings and employment opportunities (among others, Borjas, 1994; Peri and Sparber, 2009; Dustmann et al., 2016; Peri, 2016). For the sending country, the characteristics of emigrants have implications for domestic income levels and growth opportunities (e.g., due to absent productive household members, remittances, and knowledge transfer back to the home country).

Previous literature on the selectivity of migrants has almost exclusively focused on educational attainment and earnings as proxies for migrant skills (see Appendix B). Our paper is the first to study how migrants are selected on occupational skills, that is, human capital acquired through performing tasks associated with the job. Occupational skills reflect the knowledge and capabilities relevant in the labor market more directly than educational attainment, which is typically fixed after labor-market entry and is therefore uninformative regarding skill developments during the career. Occupational skills are also more specific than earnings, which presumably reflect all sorts of observed and unobserved skills. Therefore, using occupational skills to study migrant selection leads to better interpretable results because we can trace skill differences between migrants and non-migrants back to occupational choices.

This paper makes four main contributions. First, we introduce the "task framework" (Autor et al., 2003; Acemoglu and Autor, 2011) in the literature on migrant selection.[2] This approach describes each occupation in terms of the skill set required to accomplish the job tasks,[3] allowing us

[1]Recent estimates suggest that one-half of all migration movements to OECD countries are for work-related reasons (OECD, 2016b). This counts migration within free movement areas (e.g., the European Union) as being work-related, since having a job in the destination country is a typical requirement to establish residence in another member state.

[2]Cortes (2008) and Peri and Sparber (2009) were the first to use the task approach for studying migration. They highlight differences in job task assignments of U.S. natives and immigrants as a major reason why both groups appear not to directly compete with each other in the U.S. labor market.

[3]While earlier literature has argued that human capital is specific to firms (e.g., Jacobson et al., 1993), industries (e.g., Neal, 1995; Parent, 2000), or occupations (Kambourov and Manovskii, 2009), more recent evidence shows that human capital is rather specific to the basic tasks performed in occupations (e.g., Gibbons and Waldman, 2004; Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010; Nedelkoska et al., 2017).

to group occupations by *multiple* skills.[4] This provides a more nuanced picture of the selectivity of migrants. For example, if selection on different skill dimensions yields opposing patterns, assessing selection based on just a single skill dimension (e.g., education) leads to results that are difficult to interpret or even misleading (Borjas, 1991; Dustmann and Glitz, 2011).[5] Second, we document substantial migrant selection on occupational skills at the national level. We find the same pattern within very homogeneous regional labor markets and for all education levels. Third, we provide an economic rationale for the observed selection pattern based on differences in labor-market returns to occupational skills across borders. Fourth, we show that occupational choices and acquired skills are more important for understanding the role of economic benefits in the migration decision than other worker characteristics currently used for calculating migration benefits (e.g., Ambrosini and Peri, 2012; Kaestner and Malamud, 2014).

To investigate emigrant selection on occupational skills, we use the case of migration from Mexico to the United States. Mexican migrants 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). Importantly for our study, Mexico is the first major emigration country that provides detailed information about the job task requirements of its workforce through a representative worker survey (CONOCER).[6] We use a principal component analysis (PCA) to express the occupational skill space in Mexico along two dimensions: *manual* skills and *cognitive* skills. Manual skills are related to, for example, physical strength and using machinery and tools. Cognitive skills capture skills that are related to, for example, problem-solving, proactivity, and creativity.[7] From Figure 1, it is apparent that manual and cognitive skills indeed reflect two distinct skill dimensions: While the two skills are negatively correlated, individuals can also have high / low values of both skills at the same time. By combining CONOCER data with data from the U.S. O*NET, we construct skill measures of Mexican workers that are interpretable within the skill distribution of

[4]The task framework takes into account that there are large differences in the skill requirements of occupations within commonly used occupational categories (e.g., the blue/white collar dichotomy) (Ingram and Neumann, 2006; Poletaev and Robinson, 2008; Yamaguchi, 2012; Robinson, 2018). At the same time, it reveals similarities in task content that cross occupational boundaries, which are not visible from even very detailed occupational classification schemes (Autor, 2013).

[5]Using the case of German university graduates migrating abroad, Parey et al. (2017) show that there is positive selection on university grades (as a measure for education) for all migrant groups. However, using predicted earnings to measure skills, they find that graduates moving to less equal countries than Germany are positively selected and graduates moving to more equal countries are negatively selected. Moreover, Gould and Moav (2016) have found a non-monotonic pattern in the probability of migration as a function of residual wages, which cannot be explained by a one-dimensional skill measure.

[6]Thus far, representative data on the nature of jobs are available only in countries known for receiving large numbers of migrants, for instance, in Germany (Qualification and Career Survey), the United Kingdom (British Skills Survey), and the United States (e.g., Dictionary of Occupational Titles and its successor O*NET). See Autor (2013) for an overview.

[7]This differs from the notion of "cognitive skills" in education economics, which usually refers to IQ or test scores from math and reading assessments (e.g., Almlund et al., 2011; Hanushek et al., 2015).

U.S. workers. Thus, one unit of skill in Mexico has the same interpretation as one unit of the same skill in the United States. This allows for a comparison of labor-market returns to occupational skills across borders to assess the role of migration benefits for migrant decisions. By virtue of the fact that CONOCER was designed to be similar to the U.S. O*NET, we achieve scale comparability of the skill measures by *(i)* selecting questions from CONOCER that were asked in the same fashion also in O*NET, and *(ii)* using the loadings obtained from a PCA on the O*NET data to express Mexican skills in the U.S. skill metric. Using the same loadings for the construction of skills of Mexican and U.S. workers ensures that the only difference in the skill measures stems from differences in survey responses.[8]

We merge the skill measures at the detailed occupational level with individual-level Mexican worker 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).[9] These datasets allow identifying migrants from Mexico to the United States and additionally contain rich pre-migration information on worker characteristics (including labor-market history, earnings, age, education, gender, and marital status). Due to the longitudinal nature of the worker data, our measures of cognitive and manual occupational skills are based on several pre-migration occupations to capture skill acquisition through learning-by-doing; that is, a worker who repeatedly performed manual (cognitive) tasks is likely to have developed more manual (cognitive) skills. Throughout, we focus our attention on the migration decisions of Mexican males because of females' low labor-market participation rates (Kaestner and Malamud, 2014).

Comparing the occupational skills of migrants and non-migrants, we document that Mexican migrants to the United States are positively selected on manual skills, that is, migrants have higher manual skills than non-migrants, and are negatively selected on cognitive skills, that is, migrants have lower cognitive skills than non-migrants. In terms of magnitude, we find a 18% increase in migration propensity for a one-decile increase in manual skills (e.g., corresponding to the manual-skill distance from a cook to a carpenter). In contrast, migration propensity drops by 16% for a one-decile increase in cognitive skills (e.g., from a medical technician to a sales worker).

The observed pattern of selection on occupational skills holds within detailed education categories, showing that it is not driven by low-educated workers (employed in high-manual low-cognitive jobs in Mexico). Importantly, the selection pattern also holds within narrowly defined labor markets. In this analysis, we compare Mexican migrants and non-migrants working in the same broader occupation (three-digit level), industry (four-digit level), state, and year, resulting in more than 226,000 labor market segments. Thus, our results do not merely reflect that Mexicans are more likely to migrate in certain years (e.g., those with negative labor-market shocks), regions

[8]Results are similar when using PCA-loadings of CONOCER to construct skills (see Appendix C.D).

[9]Below, we devote considerable attention to discuss the implications of assigning Mexican workers the average skills in their occupation (see Section II.C).

(e.g., those close to the U.S. border), industries (e.g., manual-intensive industries), or occupational groups (e.g., agriculture).

We rationalize the observed selection pattern in a Roy/Borjas-type selection model (Roy, 1951; Borjas, 1987) with two related skills.[10] Intuitively, as in the original Roy/Borjas model, individuals choose the country that offers the highest reward to their skills. Our empirical findings are consistent with the model's predictions, because labor-market returns to manual (cognitive) skills for Mexicans are higher (lower) in the United States than in Mexico. We also provide direct evidence that the allocation of occupational skills is responsive to economic incentives by showing that differential returns to occupational skills between the United States and Mexico are a significant predictor of migration. One of our most striking findings emerges when we compare returns to occupational skills with previously used measures of economic benefits of migration. Ambrosini and Peri (2012) and Kaestner and Malamud (2014) explain migration decisions by differential returns to basic worker characteristics along the dimensions education, age, and marital status, which are readily observed in census data and are comparable across borders. We find that differential returns to occupational skills are considerably more strongly related to migration than differential returns to basic characteristics and in fact explain large part of the latter's association with migration. The above studies have also used differential returns to basic worker characteristics to explain why Mexican migrants are predominantly coming from the bottom of the earnings distribution. We again find that differential returns to occupational skills clearly outperform differential returns to basic characteristics in explaining the negative selection on earnings.

Moreover, differential returns to occupational skills positively predict migration within education categories. The correlation is strongest at intermediate levels of education, which may explain the finding of intermediate selection on education in some previous studies (e.g., Chiquiar and Hanson, 2005; Fernández-Huertas Moraga, 2011; Kaestner and Malamud, 2014). Documenting the same pattern of selection on occupational skills within each education category also supports the notion that Mexican migrants are imperfect substitutes for equally educated U.S. natives because they are selected on tasks they are best able to perform (Peri and Sparber, 2009). This result further suggests that not accounting for the importance of (returns to) occupational skills for the migration decision may explain the inconsistent conclusions of the cross-country literature on whether the Roy-Borjas model can explain migrant selection on education (e.g., Belot and Hatton, 2012; Grogger and Hanson, 2011).

To further strengthen the point that returns to occupational skills are crucial for understanding the economic motives for migration, we analyze returns to skills within narrowly defined labor-market segments. We observe that within these segments migrants and non-migrants have the same

[10] Dustmann and Glitz (2011) develop a Roy/Borjas model with two independent skills and Dustmann et al. (2011) formulate a multi-dimensional skill model in the context of return migration.

average earnings in Mexico. Thus, both arguably have similar opportunity costs of migration (i.e., foregone earnings in Mexico) and similar capabilities to bear migration costs (e.g., access to credit). Moreover, since we compare migrants and non-migrants in the same (three-digit) occupation, both also have similar legal migration opportunities (i.e., similar availability of visa categories). Any positive relationship between differential returns to skills and migration should therefore reflect perceived economic benefits in the United States. We find such positive relationship for differential returns to occupational skills, but not for differential returns to basic worker characteristics. This indicates that migrants' occupational choices and acquired skills are more important to capture the economic motives for migration than the worker characteristics emphasized in previous literature. However, we also acknowledge that causality is clearly difficult to establish without exogenous variation in returns to skills.

The task framework purports that occupational task requirements provide meaningful information about a worker's actual set of skills. This approach builds on the notion that workers choose the occupation in which their skill bundle is valued the most (Roy, 1951; Acemoglu and Autor, 2011). Our results strongly support this idea. For example, our finding that differential returns to (observed) occupational skills can explain negative earnings selection and are strongly positively correlated with migration both at the national level and within narrow labor markets indicates that workers have indeed acquired the skills to carry out the tasks required in their occupation. Moreover, by exploiting information on the individual's occupation at the start of his career in an instrumental-variable analysis, we find substantial path-dependency in job choices, implying that workers have accumulated the skills needed in their current occupation during their career. Complementary evidence shows that Mexican workers also tend to switch to skill-related occupations when migrating to the United States.

The remainder of the paper is structured as follows. Section II introduces the data and describes how we construct the occupational skill measures. Section III develops a Roy/Borjas-type selection model with two related skills, derives the model predictions, and tests them empirically for Mexican emigrants to the United States. Section IV presents the results regarding selection on occupational skills. Section VI discusses alternative explanations for our results and relates our work to previous studies on international migrant selection. Section V provides evidence that returns to occupational skills are crucial for understanding economic benefits to migration and for explaining selection on earnings. Section VII concludes.

II Data and Construction of Occupational Skill Measures

This study's primary innovation is its use of detailed information on the skill structure of Mexican occupations provided by the CONOCER survey. In this section, we describe the CONOCER data and the construction of the occupational skill measures based thereon. To investigate the selection on occupational skills of Mexican emigrants, we link these measures to rich Mexican micro-level datasets that permit identifying migrants to the United States. These datasets are also described below.

A Measuring the Skill Content of Mexican Occupations

In 2012, the Mexican government fielded the CONOCER survey to collect comprehensive information about the competencies required in the universe of occupations in Mexico. CONOCER is a representative worker survey of 17,250 respondents in 443 occupations (four-digit level). In 97% of all occupations, the number of respondents is 30 or more. The survey captures an exceptionally large set of job content aspects, grouped into eight domains (*use of tools*, *physical abilities, cognitive & social skills*, *traits*, *responsibility*, *skills, abilities*, and *knowledge*) with more than 100 questions in total, thus providing detailed information about the nature of jobs that is directly comparable across all occupations. CONOCER was designed to be comparable to the U.S. O*NET, a survey that has been used frequently in prior research (e.g., Acemoglu and Autor, 2011; Firpo et al., 2011; Autor and Dorn, 2013; Kok and ter Weel, 2014).[11] Similar to O*NET, CONOCER contains information about how important a particular job aspect is in daily work, ranging from 1 ("dispensable") to 5 ("essential").[12] To assess the skill content in each detailed Mexican occupation, we aggregate the responses from individual to occupational level by taking occupational averages at the four-digit level (for a similar aggregation with German task data, see Gathmann and Schönberg, 2010).

Using task data to construct occupational skill measures has the advantage that it identifies task commonalities that cross occupational boundaries, which are concealed in standard occupational classification schemes that group occupations roughly according to the services that they provide, such as health services, production, and analysis (Autor, 2013). It also permits cross-country comparisons because we can abstract from country-specific occupational titles and job classifications systems by creating a representation of jobs in terms of their actual task content. For instance, similarly worded occupational titles in Mexico and the United States may represent very different skill requirements in some cases—e.g., a cashier in Mexico may need more manual skills than a cashier in the United States, whose job is more computerized. At the same time, skill requirements

[11]The Occupational Information Network (O*NET), developed under the sponsorship of the U.S. Department of Labor, is an ongoing data collection program that surveys employees and occupational experts in the United States. Ever since the O*NET replaced the DOT in 1998, it has been the primary source of information about job content in the United States. O*NET is designed according to the content model, which explicitly distinguishes between fixed characteristics of employees (e.g., physical and cognitive abilities, values and work style preferences), acquired characteristics (knowledge and different categories of skills), and experience. Specifically, O*NET has 52 variables related to abilities, 35 to skills, 41 to generalized work activities, and 16 to work styles.

[12]The importance scales in O*NET use the same range of values and are worded similarly.

in occupations titled differently in both countries may actually be very similar. While comparability of skills across borders is not important for our results on emigrant selection, the property that one unit of skill in Mexico has the same interpretation as one unit of the same skill in the United States is a prerequisite for our analysis of the role of differential returns to skills between Mexico and the United States in explaining migration (see Section V).

In general, occupational information surveys such as CONOCER and O*NET are designed to describe a wide range of information on worker and job characteristics. In our analysis, however, we want to extract a set of fundamental occupational skills instead of identifying only a summary measure of task requirements. This is important because our final skill measures should be comparable across borders, which means that they should not capture country-specific occupational particularities. In Appendix C.A, we provide a detailed step-by-step description how we construct our measures of cognitive and manual skills. We start by acknowledging the fact that survey items in CONOCER and O*NET are organized into different domains, covering key attributes and characteristics of workers and occupations. While both CONOCER and O*NET capture similar job content information, they inevitably differ to some degree in survey organization, detail, and emphasis on specific domains. To ensure that we match the right survey items in CONOCER and O*NET, we first construct a correspondence between the domains in both surveys. Based on content similarity, we match the domains *use of tools, physical abilities, cognitive & social skills,* and *traits* in CONOCER to the corresponding domains in O*NET (Appendix Table C1).[13] For example, we match the domain *use of tools* comprising items such as use of agricultural machinery, industrial machinery, and transportation equipment from CONOCER to the domain *work activities* in O*NET comprising items such as operating vehicles and controlling machines and processes. The next step is to construct a one-to-one mapping of survey items in CONOCER to those in O*NET (Appendix Table C2). The mapping uses only similarly worded questions in both surveys.[14] In this step, we separate items that are related to the *use of office equipment* domain from the *use of tools* domain because both arguably represent independent variation.

Given that responses in each domain are highly correlated, we use a principal component analysis (PCA) on the items within each domain (*use of tools, use of office equipment, physical abilities, cognitive & social skills,* and *traits*) to reduce data dimensionality.[15] The advantage of working with separate groups of related questions is that this does not impose an arbitrary assumption of

[13]The CONOCER domain *responsibility* has no counterpart in O*NET. Questions in the domains *skills*, *abilities*, and *knowledge* are only given to either high-skilled or low-skilled individuals and are therefore not used.

[14]Because we use only a subset of questions from both surveys, we do not take into account all available information. However, alternative skill measures based on the full set of CONOCER questions are highly correlated with those constructed from the subset of questions ($\rho > 0.86$).

[15]Ingram and Neumann (2006) use a related data reduction technique, factor analysis, in constructing measures of skills from 53 variables on tasks collected in the Dictionary of Occupational Titles, the predecessor of O*NET. Yamaguchi (2012) and Autor and Handel (2013) employ PCA to create measures of job tasks.

orthogonality of skill measures. We rely on the first principal component of each item to derive a domain-specific skill measure, which captures 50–95% of the shared variation within a domain. Because the CONOCER domains of *cognitive & social skills* and *traits* map to the same domain in O*NET, we average these two intermediate skill measures and keep the label of *cognitive & social skills*. Thus, our PCA-based data reduction leads to four intermediate skills: use-of-tools skills, physical skills, cognitive & social skills, and use-of-office-equipment skills.

However, these skills still share common variation as can be seen by a high correlation between use-of-tools skills and physical skills, and between cognitive & social skills and use-of-office-equipment skills (Appendix Table C4). For the tractability of the analysis, it is desirable to reduce the data dimensionality further by exploiting the correlation between the intermediate skills. Moreover, the intermediate skills may still not be fundamental enough to be comparable across borders. We therefore repeat the PCA on the intermediate skill scores, which leads to our final set of two skill dimensions. Specifically, we take the first principal component of use-of-tools skills and physical skills to measure fundamental manual skills, and we take the first principal component of cognitive & social skills and use-of-office-equipment skills to measure fundamental cognitive skills.[16]

To make the Mexican skill measures directly comparable to similarly constructed skill measures for the United States, we use the loadings from one survey to calculate the skill scores in both surveys. The construction of comparable skill measures is rendered possible because CONOCER and O*NET have the same response scale for the questions (by virtue of the similarity in survey designs) and because of the one-to-one mapping of survey items between both surveys.[17] Our final skill measures use the loadings from the O*NET analysis (Column 4 of Table C3) and apply them to the corresponding items in the CONOCER survey (skills of workers in Mexico) and in the O*NET survey (skills of workers in the United States). Using the same loadings ensures that cross-country differences in the skill scores only stem from the differences in responses.[18] The reason for denominating Mexican skills in the U.S. skill metric is that our economic explanation of the migration behavior is based primarily on the idea that Mexicans evaluate the value of their skills in

[16]While yielding a qualitatively similar pattern of results, Appendix C.B shows that the results are more consistent across different samples when we use skill measures from this two-step PCA approach instead of skill measures derived in just a single step (i.e., when not first running a PCA on the items within each domain). This suggests that the PCA has problems to identify fundamental measures of cognitive and manual skills when we ignore the domain (i.e., the context) of the items. In addition, the number of items per domain varies, which contributes to uncertainty about the relative contribution of each domain in the final scores.

[17]The fact that loadings obtained from separate analyses of CONOCER and O*NET are generally very similar (Appendix Table C3) suggests that the items in both surveys measure similar skill dimensions. Appendix C.D shows that CONOCER-based skill scores and O*NET-based skill scores are highly correlated ($\rho = 0.87$ for manual skills and $\rho = 0.99$ for cognitive skills). While there are differences in the intermediate score of use-of-tools skills across surveys, we show that they do not affect our conclusions.

[18]In Appendix C.D, we show that the results obtained from using either O*NET-based or CONOCER-based skill scores are qualitatively similar.

the U.S. labor market; thus, they compare their skills to those of workers in the United States.[19] The resulting skill scores allow us to interpret the skills of Mexican workers within the skill distribution of U.S. workers. To facilitate interpretation, we convert the raw scores to a percentile scale based on the distribution of the scores in the 2010 U.S. Census.

Figure 1 depicts the occupational landscape of the Mexican population along cognitive and manual occupational skills. For example, a street vendor is at the 37th percentile of the U.S. manual skill distribution and at the 5th percentile of the U.S. cognitive skill distribution. In contrast, an engineer has both higher manual skills (75th percentile) and higher cognitive skills (91st percentile) than a street vendor. An architect has even higher cognitive skills than an engineer (95th percentile), but somewhat lower manual skills (70th percentile). We observe a negative correlation between the two types of skills (at the occupational level: $\rho = -0.19$ / weighted by number of individuals: $\rho = -0.46$), but we also see plenty of variation in the other skill for a given level of cognitive or manual skills.[20]

Figure 1 also illustrates that the average Mexican worker, relative to an average worker in the United States, has high manual skills and low cognitive skills (indicated by the red lines). Moreover, while the distribution of cognitive skills in Mexico covers the entire U.S. skill range, the distribution of manual skills is compressed and ranges mainly between the 33rd and 84th percentile of the U.S. manual skill distribution.[21] While there are several potential reasons for the high dispersion of the U.S. manual skill distribution, a likely reason is the skill-biased employment structure in the United States, which leads to a higher task specialization in the U.S. labor market as compared to Mexico.[22] One explanation are high opportunity cost of skilled workers in the United States to perform simple tasks, which results in a more specialized market for services that are close substitutes for home production activities (personal care services, housekeeping, etc.) (Cortés and Tessada, 2011; Mazzolari and Ragusa, 2013). Relatedly, Peri and Sparber (2009) show that task specialization among U.S. natives and migrants leads to an expansion of occupations with high communication skill intensity among natives and high manual skill intensity among migrants (see also, Peri, 2012; Peri and Sparber, 2011, for further evidence on immigration-induced task specialization), increas-

[19] Appendix C.D provides suggestive evidence that this is indeed the case.

[20] Both occupational skill measures also vary widely for a given year of schooling (see Appendix Figure A1(a)). While one standard deviation in manual skills, which varies between 10–15 percentiles across year-of-schooling categories, only increases mildly in worker education, cognitive skills show a much wider spread for better-educated workers. But even at low levels of educational attainment there is substantial variation in cognitive skills of at least 15 percentiles. This pattern looks very similar when we depict the variation in occupational skills for each decile in the earnings distribution (see Appendix Figure A1(b)). Thus, there is considerable variation in cognitive and manual skills both at the bottom and at the top of the earnings distribution.

[21] Appendix Table C11 shows that the results do not depend on whether we use the U.S. population or the Mexican population to convert the raw scores into percentile measures.

[22] For example, U.S. carpenters rank at the 92th percentile of the U.S. manual skill distribution, while Mexican carpenters rank at the 74th percentile in the same distribution. However, the U.S. carpenter ranks only at the 15th percentile in the U.S. cognitive skill distribution, while the Mexican carpenter ranks at the 32th percentile.

ing the variance in occupational skills. Moreover, countries with a higher GDP per capita usually have a more diverse set of products and services (Cadot et al., 2011; Imbs and Wacziarg, 2003), which could also translate into a higher variance in occupational skills.

Table 1 shows the six top and six bottom Mexican occupations in terms of cognitive and manual skill content. Occupations like managers/coordinators, municipal authorities, hotel managers, specialists in HR, secondary school teachers, and professors score high on cognitive skills, while operators of agricultural machinery, farm managers and foremen, support workers in agriculture, miners, and loggers have high manual skills. Log splitters, cattle breeders, workers in certain crops, garbage collectors, and workers in maize/beans have the lowest cognitive skills. Software developers, photographers, fiber weavers, and street vendors have the lowest manual skills. Two observations emerge from this table. First, our PCA-based skill measures yield a sensible classification of jobs along the two skill dimensions.[23] Second, even within the top-six and bottom-six occupations with respect to one skill dimension, there is also variation in the other dimension. For example, within the bottom-six manual skill occupations are street vendors who need very little cognitive skill for their jobs and software developers who need very high cognitive skills.

B Identifying Mexican Emigrants

Our main source of worker data is the quarterly National Survey of Occupation and Employment (Encuesta Nacional de Ocupación y Empleo—ENOE), which has been used extensively to study the selection of Mexican emigrants to the United States (see, e.g., Rendall and Parker, 2014; Villarreal, 2016). The survey is conducted from Q1/2005–Q3/2014 by the the Instituto Nacional de Estadística, Geografía e Informática (INEGI), and its structure is similar to the Current Population Survey (CPS) in the United States. Thus, Mexican households are surveyed for five consecutive quarters and the survey reports socio-demographic variables, such as age, gender, educational attainment, occupation, and earnings. Importantly, the panel structure of the survey allows the identification of emigrant characteristics before the move.[24]

In all specifications based on the Mexican Labor Force Survey, we define *migrants* as males between 16 and 65 years of age, who lived in Mexico in quarter t and who left for the United States in quarter $t + 1$. *Mexican residents*, on the other hand, are males aged 16 and 65 years living in Mexico in both quarter t and quarter $t + 1$. We restrict our analysis to males because of Mexican women's high rates of nonparticipation in the labor market (Kaestner and Malamud, 2014).

[23]The perhaps surprising observation that software developers have lower cognitive skills than municipal authorities and hotel managers can be explained by the fact that our measure of cognitive skills also relates to characteristics that are non-cognitive in nature (e.g., teamwork, self-control, and perseverance). See Appendix C for details and a discussion.

[24]Percentile ranges of occupational skills in the Mexican Labor Force Survey are almost identical to those in the Mexican Census presented in the previous section.

The main advantage of the Mexican Labor Force Survey is that it is nationally representative and reports occupational information at a very detailed (i.e., four-digit) level, which is key to our approach.[25] In further analysis, we check the robustness of our results in three other surveys that are also commonly used to identify Mexican migrants (see Appendix D for a detailed description): first, the Quarterly National Labor Survey (Encuesta Nacional de Empleo Trimestral–ENET), the predecessor of ENOE, which covers the period from 2000 to 2004 (see, e.g., Fernández-Huertas Moraga, 2011, 2013, who use ENET for studying migrant selection); second, the Mexican Migration Project (MMP), a retrospective life history survey representative for immigrant-sending communities (see, e.g., Orrenius and Zavodny, 2005, who use the MMP for studying migrant selection); third, the Mexican Family Life Survey (MxFLS), which has the main feature that it follows entire migrating households abroad (see, e.g., Ambrosini and Peri, 2012; Kaestner and Malamud, 2014, who use the MxFLS for studying migrant selection).

C Measuring Occupational Skills in Longitudinal Worker Data

Our individual-specific measures of cognitive and manual skills are based on all occupational information available in period t (see Yamaguchi, 2018, for a similar approach to measure worker endowment of task-specific skills). Specifically, the skill score in period t is a simple average of the current and all previously reported occupations.[26] In ENOE and ENET, we can use at most four pre-migration quarters to measure skills.[27] In MMP, where we have information on an individual's complete job history, we use the entire pre-migration history to construct the skill measures. In MxFLS, we use the occupation of the current job, the job five years prior to the survey, and the first job.

Relying not only on the task content of the current job, but on the history of previously held occupations, has several important advantages. First and foremost, our measures can more reliably be interpreted as skills possessed by workers (vis-à-vis tasks performed at work) because they reflect skill acquisition through learning-by-doing. Thus, we assume that the more experience a worker accumulated in performing, say, cognitive tasks, the higher the worker's level of cognitive skills. Second, it is not clear which single occupation is more appropriate for measuring occupational skills than an average over all observed occupations. The last pre-migration occupation is endogenous to the migration move if individuals regard it as particularly suitable for emigration

[25]In Q2/2012, a new occupational classification system (Sistema Nacional de Clasificación de Ocupaciones—SINCO) was introduced, replacing the Mexican Classification of Occupations (Clasificación Mexicana de Ocupaciones—CMO). We use crosswalks between occupational codes to make the coding comparable over time. Details are provided in Appendix D.B.

[26]In Appendix G, we show that our results hold for various definitions of the relevant occupation (most importantly, last pre-migration occupation and first occupation upon labor-market entry).

[27]In ENOE, we observe more than one pre-migration occupation for slightly more than half of the migrants (52%). For 24% of the migrants, we observe more than two pre-migration occupations.

(e.g., for visa considerations).[28] Similarly, a negative labor-market shock (e.g., plant closures) may push workers into a less desirable occupation, and they therefore decide to migrate. Using the first occupation at labor-market entry, although likely unaffected by the (future) migration decision, has the problem that occupational skills are not fully developed at this stage and that there is the potential for imperfect job matches (e.g., Jovanovic, 1979; Altonji and Pierret, 2001; Hanushek et al., 2015). Third, using a cumulative skill measure allows us to consider individuals who are unemployed in the current period.[29] This is a major advantage because unemployed individuals (with missing earnings information) may migrate because of their unemployment status.

Because we use a worker's occupational history for constructing the occupational-skill measures, these measures vary at the individual level. However, our results mainly rely on between-occupational variation in skills because we always assign workers the average skills for their occupation (in the baseline, at the four-digit level). This unavoidable limitation has implications for the analysis of migrant selection on occupational skills (see also Abramitzky et al., 2012, for a discussion in the context of migrant selection based on average occupational earnings). Positive migrant selection, for instance, could be generated either by high migration rates among Mexicans from occupations with high average occupational skills or by high migration rates among Mexicans at the top percentiles of the occupational skill distribution *within* their occupation. An analogous argument holds for negative selection. However, we are confident that inferring a worker's actual skill level (which is unobservable to us) from the average skill level in his occupation is no first-order concern. In particular, the work by Autor and Handel (2013) shows that individual-level task measures perform as well in predicting wages as the same task measures averaged by occupation. Furthermore, although we cannot observe worker skills at the individual level, our skill measures are based on occupational information in very fine categories (443 occupations, four-digit level). In Appendix D, we show that there is meaningful variation in our measures even within three-digit occupations, suggesting that we capture the skill heterogeneity within broader occupational categories. It is also reassuring that the selection pattern that we observe in the data is very similar when we condition on occupation fixed effects at the three-digit level (see Section IV.A).

III Theory of Emigrant Selection

To guide our thinking about how Mexican migrants are selected on occupational skills, we develop a variant of the Roy/Borjas model (Roy, 1951; Borjas, 1987) of international migrant selection that accommodates two related skills.[30] In line with the basic variant of the Roy/Borjas model, we show

[28] In Section VI, we discuss the possibility that skill formation is endogenous to migration propensity.

[29] We ignore skill depreciation due to unemployment because it is unclear how fast occupational skills depreciate when individuals are not working.

[30] See Dustmann et al. (2011) for a Roy/Borjas model with two skills in the context of return migration. Dahl (2002) and Kennan and Walker (2011) develop models of internal migration and show the importance of expected returns for

that Mexican workers should allocate their skills to the country where these skills are valued the most. We then estimate the returns to occupational skills for Mexican workers in Mexico and the United States to derive theory-based predictions for the pattern of selection of Mexican migrants.

A A Selection Model with Two Related Skills

Assume that all workers are characterized by two skills labeled z_1 and z_2, for example, cognitive skills and manual skills, which are drawn from the bivariate normal distribution with the mean vector $\boldsymbol{\mu}$ and the covariance matrix Σ:

$$\text{(1)} \qquad \mathbf{z} \sim N(\boldsymbol{\mu}, \Sigma)\,, \quad \boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \quad \Sigma = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}.$$

Skills may be correlated, so $\rho \neq 0$ in general.

Occupations in the economy are represented by ordered pairs of task intensities $\mathbf{x} = (x_1, x_2) \in \mathbb{R}^2$, where x_i is the intensity of task i. Performing task i with highest productivity requires supplying a skill input of the same type and quantity x_i. Every worker with a skill endowment $\mathbf{z}$ will choose an occupation $\mathbf{x}$ that yields the highest wage rate, which is equivalent to minimizing the skill mismatch $\|\mathbf{z} - \mathbf{x}\|$. Labor demand in every occupation $\mathbf{x}$ is perfectly elastic. In this setting, workers are perfectly matched[31] and occupations, tasks, and skills are interchangeable.[32]

As in Roy (1951), we assume that productivity is log-normally distributed. We further assume that when skills and tasks are perfectly matched, the log marginal product of labor is a linear function of skills (Welch, 1969; Dustmann et al., 2011). Together these assumptions imply that the earning capacity w of an individual with a skill vector $\mathbf{z}$ in a location j is given by:

$$\text{(2)} \qquad \log w^j = \tfrac{1}{2}\mathbf{p}^j \cdot (\mathbf{z} + \mathbf{x}) + \varepsilon, \qquad j \in \{\text{abroad, origin}\},$$

where $\mathbf{p}^j$ is a vector of returns to skills or returns to tasks (equivalently, skill or task prices)[33] and ε is an independently distributed disturbance term which reflects variation in wages unrelated to skills (e.g., luck). (The disturbance term is assumed to be location-invariant, but none of the results change when allowing for location-specific disturbances whose distributions are independent of the migration decision.

[31] In the empirical part, we explore potential mismatch between a worker's skill endowment $\mathbf{z}$ and the occupational skill requirement $\mathbf{x}$ due to demand side labor-market frictions (Section IV.C) and due to skill-specific labor-market shocks or imperfect job matches early in the career (Appendix J). The analysis shows that skill mismatch is unlikely to affect our results.

[32] All results regarding migrant selection continue to hold when—instead of perfect matching of skills and tasks—occupational sorting is on *comparative advantage*. See Appendix E.A for details.

[33] We refer to p_i simply as the "return to skill" for skill i. It does not, however, correspond to a rate of return calculation, not only because of the general arguments in Heckman et al. (2006), but also because we have no indication of the cost of achieving any given level of skill.

the distribution of skills.)[34] From these assumptions, it follows that workers in more task-intensive occupations earn more, as do more skilled workers in general. Returns to skills may differ across locations, due to, for example, differences in production technology and labor-market conditions.[35] In the baseline version of the model, we assume that migrants suffer no penalty for transferring skills across borders, so they will choose the same job in both locations. We discuss changes in the model predictions when relaxing the assumption of perfect skill transferability in Section III.B.

Every worker decides whether to stay in the location of origin or to migrate by comparing earning capacity between both locations (Sjaastad, 1962; Borjas, 1987). Migration takes place when earnings abroad net of migration costs κ exceed earnings in the location of origin. Following Borjas (1987), we assume that migration costs are the same constant fraction of income for every migrant. Equation (3) summarizes the migration decision.

$$\text{(3)} \qquad \text{Migrate} = \begin{cases} 1 & \text{if } \log w^{\text{abroad}} - \kappa > \log w^{\text{origin}} \Leftrightarrow (\mathbf{p}^{\text{abroad}} - \mathbf{p}^{\text{origin}}) \cdot \mathbf{z} - \kappa > 0 \\ 0 & \text{otherwise} \end{cases}$$

To simplify the notation, we define $\lambda_i \equiv \Delta p_i \equiv p_i^{\text{abroad}} - p_i^{\text{origin}}$ as the difference in returns to skill i between the location abroad and the location of origin.

Migrants are *positively selected* on skill i whenever $\mathbb{E}[z_i|\text{Migrate} = 1] > \mu_i$, implying that the average skill level of migrants is higher than the average skill level of non-migrants. Migrants are *negatively selected* on skill i whenever $\mathbb{E}[z_i|\text{Migrate} = 1] < \mu_i$, implying that the average skill level of migrants is lower than the average skill level of non-migrants. When conditional and unconditional means are equal, there is no migrant selection.

Given the assumptions above, the mean of skill 1 for migrants equals

$$\text{(4)} \qquad \mathbb{E}(z_1|\text{Migrate} = 1) = \mu_1 + (\lambda_1 + \lambda_2 \beta_{2,1}) \frac{\sigma_1^2}{\sigma} \frac{\phi(d)}{1 - \Phi(d)},$$

where $\beta_{2,1} = \text{Cov}(z_1, z_2)/\text{Var}(z_1)$ is the slope of a least squares regression of skill 2 on skill 1, $d = (\kappa - \lambda_1\mu_1 - \lambda_2\mu_2)/\sigma$, $\sigma^2 = \text{Var}(\lambda_1 z_1 + \lambda_2 z_2)$, and $\phi(d)/[1 - \Phi(d)]$ is the inverse Mills ratio.[36]

[34] Autor and Handel (2013) consider a more general model of earnings with occupation-specific task returns. They argue that returns to tasks and multi-dimensional skills are conceptually different to returns to uni-dimensional skill measures such as education because tasks are usually represented by bundles of activities requiring a set of skills to be carried out (for a similar argument, see Heckman and Scheinkman, 1987). Because tasks that a worker performs on the job are an application of that worker's skill endowment to a bundle of activities, it is difficult to evaluate the returns to a *specific* task or skill empirically. We discuss the estimation of returns to skills in Sections III.C and V.

[35] Lazear (2009) presents a similar model with endogenous skills in the context of firm choice.

[36] See Appendix E.B for the derivation of the selection equation. Note that the equation is equivalent to the formulation in Borjas (1987) in the special case when $\log w = z_1$, $\lambda_1 = 1$ and $\lambda_2 = -1$.

The corresponding equation for skill 2 can be obtained by symmetry, thus

$$\text{(5)} \qquad \mathbb{E}(z_2|\text{Migrate} = 1) = \mu_2 + (\lambda_2 + \lambda_1\beta_{1,2})\,\frac{\sigma_2^2}{\sigma}\frac{\phi(d)}{1-\Phi(d)}.$$

From Equation (4), it follows that the selection of migrants on skill 1 is determined by the sign of the expression $\lambda_1 + \lambda_2\beta_{2,1}$. Intuitively, this can be interpreted as the predicted benefit from relocating one unit of skill 1 abroad. The sum has two parts. The first term is the direct effect of relocating one unit of skill 1 (given by λ_1). The second term consists of the expected number of units of skill 2 that an individual has, given that he has one unit of skill 1. This quantity is given by $\beta_{2,1}$, which is multiplied by the difference in returns to skill 2 (λ_2) to obtain a monetary value. Analogously, from Equation (5), the selection of migrants on skill 2 is determined by the sign of the expression $\lambda_2 + \lambda_1\beta_{1,2}$, showing the predicted benefit of relocating one unit of skill 2 abroad.

To illustrate the model predictions with respect to migrant selection, we start with the simplest case of uncorrelated skills, that is, $\rho = 0$ (and hence $\beta_{2,1} = 0$). Here, the selection pattern for each skill i is completely determined by the differential returns between both locations, λ_i. For $\lambda_i > 0$, individuals with higher endowments of skill i tend to relocate their skills abroad, and therefore the model predicts positive selection on skill i. In Figure 2(a), there is positive selection on skill 1 in the two RHS quadrants and positive selection on skill 2 in the upper two quadrants. In contrast, for $\lambda_i < 0$, a worker receives a wage penalty from relocating skill i abroad, so the model predicts negative selection on skill i as those with higher endowments of skill i tend to remain in the location of origin. There is negative selection on skill 1 (skill 2) in the two LHS (bottom) quadrants.[37] For $\lambda_i = 0$, the reward for skill i is the same at home and abroad and there is no selection on skill i—this situation occurs along the ordinate for skill 1 and along the abscissa for skill 2.

For correlated skills ($\rho \neq 0$), the selection pattern is not only affected by the differential returns to skills, but also by the correlation between skill 1 and skill 2. The general configuration of regions of selection, however, is similar to the case of $\rho = 0$. Figure 2(b) depicts the model's predictions for negatively correlated skills (i.e., $\rho < 0$ and therefore $\beta_{2,1} < 0$).[38] In region A, negative selection on skill 2 prevails despite λ_2 being positive. The reason is that the contribution of skill 1 to the earnings differential is so large that it is more attractive to migrate for individuals with a high endowment of skill 1—and therefore on average with low endowments of skill 2. In region D, due to the negative λ_2 it becomes attractive to migrate for individuals with lower endowments of skill 2—and therefore

[37]In the bottom-left quadrant, skill price differentials are negative for both skills. From Equation (3), in this situation only individuals with skills from the left tail of the normal distribution migrate, so negative selection on both skills prevails. This result is in line with other models arguing that negative selection occurs because individuals with low productivity can insure themselves against low returns by migrating to countries with a more compressed wage distribution and/or high baseline wages (Borjas, 1987; Fernández-Huertas Moraga, 2011).

[38]This is the case of interest in this paper because the empirically observed correlation between cognitive and manual skills is negative (see Section II).

on average with higher endowments of skill 1— despite λ_1 being negative. Similarly, in region B, λ_2 is such that its contribution to the selection pattern outweighs the contribution of λ_1; and in region C, the contribution of the negative λ_1 dominates the contribution of λ_2.

The model's predictions for positively correlated skills (i.e., $\rho > 0$ and therefore $\beta_{2,1} > 0$) are shown in Figure 2(c). In region A, positive selection on skill 2 prevails despite $\lambda_2 < 0$ because λ_1 is such that individuals with a high endowment of skill 1—and therefore on average also with a high endowment of skill 2—tend to migrate. By the same logic, in region B, $\lambda_1 < 0$ is outweighed by a positive λ_2 such that individuals with a high endowment of skill 2—and therefore on average also of skill 1—find it attractive to migrate. Analogously, in regions C and D there are new combinations of (λ_1,λ_2) such that negative selection prevails for skill 2 despite $\lambda_2 > 0$ (region C) and for skill 1 despite $\lambda_1 > 0$ (region D).

For tractability and comparability to previous literature, our model is based on a number of simplifying assumptions commonly imposed (e.g., Borjas, 1987; Chiquiar and Hanson, 2005; Fernández-Huertas Moraga, 2011; Parey et al., 2017). First, migrants are risk-neutral and all uncertainty is resolved before migrating; in particular, wages in the destination country are perfectly observable. Second, migration is permanent. Third, skill formation is exogenous to migration propensity, that is, future migrants do not invest in certain skills (e.g., through occupational choices) prior to migrating because they realize that the returns to these skills are higher abroad than at home. Fourth and finally, skills accumulated at home are perfectly transferable abroad. These assumptions are unlikely to (fully) hold in reality. We discuss the empirical implications of relaxing these assumptions in Appendix G.A (risk neutrality), Appendix I (permanent migration), and Appendix J (exogenous skill formation). Skill transferability is discussed in the section below.

B Skill Transferability

The model sketched in the previous section assumes that skills transfer perfectly when workers migrate. However, suppose that migrants can only partially utilize their skills abroad, for example, due to a low degree of foreign-language proficiency (Friedberg, 2000; Bazzi et al., 2016) or due to barriers such as accreditation, licensure, or discrimination (Hendricks and Schoellman, 2018). This would lead to skill downgrading abroad (Dustmann and Preston, 2012; Dustmann et al., 2013, 2016), implying that, for instance, a medical doctor would be employed as a nurse after migration.

To assess the degree of skill transferability, we follow the common approach in the migration literature to compare immigrants' pre-migration and post-migration occupations (Chiswick et al., 2005; Akresh, 2008; Hendricks and Schoellman, 2018). We use the MMP for this comparison, because respondents report their entire occupational history (also during migration episodes). Occupational switching of immigrants is widespread; in about two-thirds of the cases (65%), Mexicans switch to a different three-digit occupation after migrating to the United States. This figure is driven mostly by changes to entirely new occupations; if we aggregate to two-digit (one-digit) occupational groups, the share of migration moves which involve an occupational switch amounts to 57% (54%).[39]

However, these occupational switches are not systematically related to changes in the quality of jobs, measured by their skill content.[40] The average distance between the pre-migration and post-migration occupation is as small as 0.7 percentiles for cognitive skills and 1.9 percentiles for manual skills.[41] The median distance is 0 for both skills. Even when conditioning on occupational switching, the average (median) distance is only 1.5 (5.1) percentiles for cognitive skills and 3.8 (7.6) percentiles for manual skills. This is roughly equal to the skill distance between occupations such as biomedical engineering and pharmacology, between carpentry and painting, or between dressmaking and shoemaking. Moreover, about 80% of occupational switches after migration are in a corridor of 30 percentiles in terms of skill distance, which is roughly the cognitive skill gap between medical doctors and nurses (i.e., the example for skill downgrading from above). This evidence suggests that although migrants tend to move to entirely new occupations, these occupations are highly skill-related to the previous ones. Overall, we observe a high degree of skill transferability when Mexicans migrate to the United States. This high skill relatedness of the pre-migration and post-migration occupation would have been masked by merely comparing job titles before and after migration, leading to wrong conclusions about the similarity of a migrant's work in Mexico and the United States.

The possibility of imperfect skill transferability can be accommodated in the model by letting $z_i^{\text{abroad}} = a_i z_i^{\text{origin}}$, with $0 < a_i < 1$, where a_i is a parameter that captures the extent of transferability for skill i across borders. Potential migrants will use the same decision rule as in Equation (3), albeit with returns abroad replaced by effective returns $\tilde{p}_i^{\text{abroad}} = a_i p_i^{\text{abroad}}$. Hence, we can use Equations (4) and (5) with appropriately defined differential returns to predict the selection pattern. Note that if migrants are not aware that they can only partially transfer their skills abroad, Equation (3) with the original differential returns applies. However, given that migration networks and relatives abroad are strong predictors of migration (McKenzie and Rapoport, 2010; Kaestner and Malamud, 2014)—because they provide information about the destination country—it seems likely that individuals in Mexico are aware of any imperfect skill transferability. Thus, returns

[39]These results are in line with recent evidence on the frequency of occupational switches of U.S. immigrants from a wide variety of countries, including Mexico (Hendricks and Schoellman, 2018).

[40]It is not possible to proxy job quality by earnings, because the MMP does not report a complete history of wages.

[41]We report absolute distances. Mexican migrants tend to switch to occupations in the United States that are less intense in both cognitive and manual skills than the pre-migration occupation. Note that the direction of the occupational switches (upward or downward) might be driven by unobserved ability or other unmeasured skills of the migrant. Using information in the MMP on the wage during the first U.S. migration spell, we find that the position of a migrant's U.S. hourly wage in the occupation-specific distribution of U.S. wages is not systematically related to the type of switch he makes (results not shown). This indicates that unexplained variation in earnings potential (e.g., due to ability or non-cognitive skills) does not drive skill upgrading or downgrading at migration.

to skills observed by the researcher likely incorporate partial skill transferability of previous migrants and can therefore be interpreted as *effective* returns in the context of the theoretical model. In Section V, we show that observed differential returns to skills are indeed strong predictors of emigration, confirming their relevance for the migrant decision.

C Model Predictions for Mexican Migration to the United States

The extended Roy/Borjas model specified in Section III.A purports that the main determinant of emigrant selection are differential returns to occupational skills. To illustrate this general mechanism and to guide intuition what to expect in the empirical analysis of selection on occupational skills of Mexican emigrants, we estimate the returns to cognitive and manual skills for Mexican residents and for recent Mexican migrants in the United States (immigrated 10 years prior to the survey year).[42] We here follow Ambrosini and Peri (2012) and Kaestner and Malamud (2014) in assuming that potential Mexican migrants form expectations about their earnings abroad based on observable characteristics of such recent migrants.[43]

We find that the returns to manual skills (skill 1) of Mexicans are higher in the United States than in Mexico (see Tables F1 and F2 in Appendix F). This seems plausible given the high supply of manual skills in Mexico (see Figure 1). In contrast, cognitive skills (skill 2) of Mexicans are better rewarded in Mexico than in the United States. Relatively low returns to cognitive skills for Mexican workers in the United States are consistent with a high supply of cognitive skills of U.S. natives or with certain high-paid cognitive jobs being unavailable for Mexican migrants (e.g., due to legal barriers). Given these differences in the returns and the fact that cognitive and manual skills are negatively correlated (see Section II), the theoretical model predicts that Mexican migrants are positively selected on manual skills and negatively selected on cognitive skills (region $+-$ in Figure 2b).

One further remark deserves attention. Our estimates cannot be interpreted as causal returns to skills, that is, we neither identify the returns that a random Mexican resident would receive in the United States, nor do we identify the causal returns of Mexican residents in Mexico. However, as long as prospective Mexican migrants are not aware of the selection bias, we can expect that migrants form expectations about their earning prospects based on observable returns of former Mexican migrants (Kaestner and Malamud, 2014). We return to this issue in Section V.

[42] See Appendix F for details on the estimation strategy and results.

[43] Ambrosini and Peri (2012), among others, compare the earnings of Mexican residents with the earnings of future Mexican migrants to the United States. Results are similar if we use the earnings of future Mexican migrants to estimate returns to occupational skills in the United States.

IV Results

This section provides evidence on the selection of migrants on occupational skills by comparing the skills of migrants and non-migrants prior to migration. We start by following the previous selection literature and compare migrants to non-migrants at the national level. We then extend the national approach by studying migrant selection within highly disaggregated segments of the Mexican labor market. To this end, we construct more than 226,000 year-state-industry-occupation cells. Even within these cells, the same pattern of selection on occupational skills as at the national level holds. This rules out that the selection pattern can be explained by year-, state-, industry-, or occupation-specific unobserved heterogeneity (or any combination thereof). We also provide further robustness checks of our results.

A Selection of Emigrants on Occupational Skills

Graphical Evidence

To investigate the occupational selection of Mexican migrants, we begin by comparing the distributions of occupational skills of migrants prior to moving to the United States to the distribution of occupational skills of non-migrants in Mexico. Figure 3 plots cumulative distribution functions (CDFs) and probability density functions (PDFs) of cognitive and manual skills by migrant status. We observe that the CDF of cognitive skills for migrants is to the left of the CDF for non-migrants.[44] This shows that migrants are negatively selected on cognitive skills along the entire skill distribution. For manual skills, the CDF of migrants is to the right of the CDF of non-migrants, indicating positive selection. These results are confirmed by the PDFs, showing that the mass of density for Mexican migrants is at the bottom (top) of the cognitive (manual) skill distribution.[45] In quantitative terms, we find that workers in ENOE are 76.6% more likely to emigrate when they belong to the bottom tertile of the cognitive skill distribution compared to having average cognitive skills (see Appendix Table A1). In contrast, workers are 55.3% less likely to migrate when belonging to the top tertile of the cognitive skills distribution than when having average skills. The opposite pattern holds for manual skills. Compared to the average, workers are 48.3% less likely to migrate when coming from the bottom tertile of the manual skill distribution and 56.7% more likely to migrate when coming from the top tertile. These results indicate that, in line with the theory outlined in Section III, Mexican emigrants to the United States are negatively selected in terms of cognitive

[44] Kolmogorov-Smirnov tests indicate that the CDFs for both cognitive and manual skills are significantly different from each other throughout. Using the test on stochastic dominance proposed by Borjas et al. (2019) confirms this result (see Appendix Figure A2).

[45] In fact, the PDFs for manual skills suggest a bimodal distribution, with peaks occurring somewhat below the median and the 75th percentile of the manual skill distribution. Further investigation shows that these spikes do not result from a single (large) occupation.

skills and positively selected in terms of manual skills.[46]

Appendix Table A1 also reports migration propensity at different points of the skill distribution in the other Mexican worker data (i.e., ENET, MMP, and MxFLS). Strikingly, the pattern of selection is very similar in all datasets in terms of both the general pattern of selection and the differences in migration propensities at different points in the skill distribution. For comparison, we also consider emigrant selection on education. Here, we observe that Mexican emigrants come mostly from the middle and bottom of the educational distribution, suggesting intermediate to negative educational selection (Fernández-Huertas Moraga, 2011).

Regression Analysis

The previous results do not take into account that individuals' occupational skills may coincide with other personal characteristics, such as education and age. To investigate the selection pattern conditional on worker characteristics, we estimate linear probability models to predict migration propensity to the United States. The dependent variable is a migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise). Because the probability of Mexicans moving to the United States differs substantially across time (due to different migration waves), datasets (due to different sampling frames), and samples, we scale the migration indicator by the sample-specific migrant share to make effect sizes comparable. Thus, coefficients are interpreted in terms of *percentage* changes relative to the average migration rate (instead of a *percentage-point* changes). We estimate the model as a pooled cross-section and include quarter-by-year fixed effects to account for temporal migration shocks. Since using individuals' occupational histories to construct occupational skills makes our skill variables individual-specific, we cluster standard errors at the household level throughout the paper.[47]

Results are presented in Table 2. We find that, on average, migration propensity is negatively associated with cognitive skills and positively associated with manual skills (Column 1). From Figure 1, it follows that there are occupations with similar levels of cognitive skills, but with very different levels of manual skills (and vice versa). We therefore include an interaction between cognitive and manual skills, which allows for a nonlinear relation of skills with migration propensity. To facilitate interpretation and avoid out-of-sample predictions, we demean cognitive and manual skills in the interaction models; that is, the marginal effect of either skill is evaluated at the mean of the other skill. The coefficients on cognitive and manual skills change only slightly when adding

[46] This selection pattern is not generated by a specific occupation or time period: it is robust to omitting one one-digit occupation at a time (results not shown) and is very similar in ENET covering the period 2000–2004 (see Appendix Figure A3). Note that there is less scope for investigating the selection pattern along the entire occupational skill distribution in MMP and MxFLS because skills are measured at a coarser occupational level in these data.

[47] Clustering standard errors at the last observed four-digit occupation somewhat decreases the precision of our estimates, but does not change our conclusions.

the interaction term, which itself turns out to be negative (Column 2).[48] The negative coefficient on the interaction term indicates that the (negative) association between cognitive skills and migration propensity is stronger at above-average manual skill levels and less strong at below-average manual skill levels. The opposite holds for the (positive) association between manual skills and migration propensity at different levels of cognitive skills; here, the association is stronger at below-average levels of cognitive skills and less strong at above-average levels of cognitive skills. These results are in line with the theoretical predictions, because they suggest that migration propensity is largest for individuals with high manual and low cognitive skill bundles. Table 3 illustrates this pattern by showing average migration propensities for high vs. low values of cognitive/manual skills with cutoffs at the median of the skill distributions. We also report the coefficient β from a linear regression of migration propensity on cognitive (manual) skills within the indicated manual (cognitive) skill category. In general, migration propensities are increasing in manual skills and decreasing in cognitive skills. However, the estimated β coefficients suggest that migration propensity is more strongly increasing in manual skills when cognitive skills are low, and is more strongly decreasing in cognitive skills when manual skills are high.[49]

For comparability with the existing literature on migrant selection, Column 3 of Table 2 shows the relationship of migration propensity with both years of schooling and age. Confirming previous results, we find that Mexican migrants are predominantly low-educated and young. This raises the concern that the estimated pattern of selection on occupational skills is partly driven by education, because years of schooling are positively correlated with cognitive skills ($r = 0.64$) and negatively correlated with manual skills ($r = -0.47$). Therefore, Column 4 simultaneously includes occupational skills, years of schooling, and age. While coefficients on the occupational skill variables are barely affected, the coefficient on years of schooling becomes very small (and even turns positive). Thus, holding the occupational skills constant, people with better education are not less likely to migrate *on average*. Given that educational decisions are important for later occupational choices, this result indicates that the negative selection on education commonly found in other studies operates through the selection on occupational skills. Of course, concerns about omitted variable bias and measurement error may invalidate such a conclusion (see Hanushek et al., 2015, for a related discussion).[50] However, this result is consistent with the work by Villarreal (2016) showing that Mexican migrants are positively selected on education within broader occupational groups.

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[48] Regressions without an interaction term confirm the selection pattern (see Appendix Table A2). Instead of using an interaction between cognitive and manual skills, we also estimate specifications that capture the nonlinear relation of skills with migration propensity through a sixth-order polynomial or decile fixed effects. The estimated selection pattern is very similar to our baseline results (see Appendix Table A3).

[49] In Appendix Table A4, we show that the selection pattern is similar when we use the four skill categories instead of linear skills.

[50] The authors describe the econometric implications of estimating the wage returns to human capital when simultaneously using years of schooling and cognitive skills as human capital measures.

The selection on occupational skills is not only statistically significant, it is also economically relevant. In our baseline specification (Column 4 of Table 2), an increase in cognitive skills by one decile, ceteris paribus, is associated with a 16% drop in the propensity to migrate. This is equivalent to comparing migration propensities of a medical technician (at the mean of the cognitive skill distribution) and a sales worker (+1 decile in cognitive skills).[51] Similarly, when manual skills increase by one decile, the propensity to migrate increases by 18%. This is equivalent to comparing migration propensities of a cook (at the mean of the manual skill distribution) and a carpenter (+1 decile in manual skills).

Selection on occupational skills might depend on the available occupations from which individuals can choose, for instance, due to the local industry structure. Columns 5–7 of Table 2 consider different labor-market definitions to show that the selection pattern also holds in rather homogeneous labor markets with similar job opportunities. In Column 5, we include birth state-by-residence state fixed effects. We find that selection within these regional labor markets (defined by state boundaries) is very similar as in the baseline model. In Column 6, we identify only from within-municipality variation by including 1,499 municipality fixed effects. Coefficients on the occupational skill measures become only slightly smaller (in absolute terms).[52]

We can also define labor markets in terms of broader occupational categories. Column 7 shows that our results cannot be explained by differences in the job content of large occupational categories, say, agriculture and services. In fact, we can control for occupation fixed effects at the three-digit level and observe a qualitatively similar selection pattern as in the baseline. In general, selection within regional labor markets leads to very similar results as in the baseline, while selection within occupational labor markets tends to be somewhat weaker. However, the broader occupational category is simultaneously determined with the detailed occupation. Thus, adding occupation fixed effects ignores a considerable part of the variation that we would like to use for identification.

One major concern is that our results are just driven by low-educated Mexicans, who have had manual-intensive jobs at home and also work in such manual jobs in the United States. At the same time, high-educated Mexicans working in cognitive-intensive jobs may not migrate because they have no access to cognitive U.S. jobs due to barriers such as accreditation and licensure or due to lacking language skills. In Table 4, we estimate our baseline model at different points in the years-of-schooling distribution. We find that migrants are positively selected on manual skills and

[51] The higher cognitive skill score of sales workers as compared to medical technicians reflects their higher level of customer interaction, which requires more interpersonal skills. In Section IV.B , we provide results showing that both *interpersonal* skills and *intrapersonal* skills are important for understanding migrant selection on cognitive skills.

[52] We also study different selection patterns of migrants from rural and urban areas (Appendix Table A5). In contrast to Fernández-Huertas Moraga (2013), who finds positive selection on actual earnings in rural Mexico and negative selection in urban Mexico, we observe a rather homogeneous pattern of selection on occupational skills across region types.

negatively selected on cognitive skills at each education level, which rules out that low-educated migrants with high-manual low-cognitive jobs in Mexico explain our results. Moreover, the result supports the findings by Peri and Sparber (2009) who show that Mexican migrants are imperfect substitutes to U.S. natives within education categories. Another concern is that ENOE does not allow to identify migrants when the entire household leaves Mexico ("invisible sample selection", see Steinmayr, 2014). Such sample selection would lead to an upward bias in our results if whole-household migration would primarily occur for households whose members have high cognitive and low manual skills. Ambrosini and Peri (2012) as well as Kaestner and Malamud (2014) show that this issue can be addressed by using the Mexican Family Life Survey (MxFLS). The survey has the main advantage that it follows entire households abroad, with re-contact rates for migrants and non-migrants as high as 90% (Kaestner and Malamud, 2014). Table G1 in Appendix G.B shows that results with MxFLS data are very similar to our baseline results using ENOE. Thus, the likely undercount of migrants in ENOE due to whole-household migration is unlikely to affect our findings. Moreover, Appendix Tables G2 and G3 show that our baseline results also carry over to MMP and ENET, indicating that the selection pattern is robust to changes in sampling design and observation period.

In Appendix G.C, we also investigate the long-run dynamics of selection on occupational skills of Mexico-U.S. migrants. Exploiting the fact that the MMP collects retrospective information on migration episodes reaching back to the 1950s, we find that the selection pattern remained highly persistent over periods of sharp increases in net migration and periods where net migration has plummeted.

B Alternative Definitions of Occupational Skills

This section discusses alternative ways to define occupational skills and their association with migration propensity. While it is beyond the scope of the paper to discuss all possibilities to organize occupational groups with the purpose to derive occupational skill measures, we highlight the results from what we consider to be the most important alternative skill configurations.

Peri and Sparber (2009) study migration-induced specialization of U.S. natives along manual-intensive and communication-intensive occupations, showing that Mexican immigration causes natives to reallocate their task supply away from manual-intensive tasks more toward communication-intensive tasks. In Column 2 of Table 5, we replace cognitive skills by communication skills.[53] These are measured by the "verbal communication" item in CONOCER and by the "oral expression" and "written expression" items in O*NET (see Appendix C.C for details). We observe that Mexican migrants are negatively selected on communication skills. This finding is not surprising

[53]We do not include an interaction with manual skills in Table 5 for the ease of exposition. Column 1 provides the baseline results of this specification.

because communication skills are certainly more difficult to transfer to the United States than are manual skills. Importantly, our baseline measure of cognitive skills does not include the verbal communication items (see Appendix C.A). Therefore, it is interesting to observe that the coefficient on communication skills drops considerably when we add cognitive skills to the model in Column 3 of Table 5. Thus, part of the relationship between communication skills and migration propensity is captured by our more general measure of cognitive skills. In fact, Appendix Table C9 shows that cognitive skills and communication skills are highly correlated ($r = 0.8$). Still, the coefficient on cognitive skills changes only little when communication skills are included, suggesting that a considerable part of the variation in cognitive skills is independent of communication skills.

Communication skills represent only a fraction of all interpersonal skills. Dividing cognitive skills into *inter*personal and *intra*personal skills (see National Research Council (2012) for an in-depth discussion of this skill categorization and Appendix C.C for further details), we study selection patterns along broader definitions of "non-manual" skills in Columns 4 to 6 of Table 5. While interpersonal skills refer to expressing ideas as well as to interpreting and responding to messages from others, intrapersonal skills refer to cognitive processes and strategies, emotions and feelings, as well as self-regulation. Thus, among the items that comprise our cognitive skill measure, we associate items such as coordination, teamwork, negotiation and persuasion, service orientation, and empathy with interpersonal skills, and items such as perseverance, self-control, problem-solving, and critical thinking with intrapersonal skills. The results indicate that both interpersonal skills and intrapersonal skills are negatively associated with migration propensity (Columns 4 and 5). Including both skills at the same time in Column 6, we observe that interpersonal skills are somewhat more strongly associated with migration propensity than intrapersonal skills. Interestingly, the coefficient on communication skills dwarfs in size and loses significance in the specification with interpersonal skills (Column 4), while communication skills remain significant when jointly included with intrapersonal skills (Column 5). This implies that communication skills—as measured in CONOCER and O*NET—are fully captured by the broader measure of interpersonal skills. Hence, focusing on communication skills alone to explain migrant selection on cognitive skills is likely too narrow.

For our baseline results, we express occupational skills of Mexican workers in the U.S. skill metric by using loadings from the PCA of the O*NET items (see Section II.A). Alternatively, we can also express the skills in the Mexican skill metric by using loadings from the PCA of the CONOCER items. In Appendix C.D, we compare the scores that result from using either skill configuration. The correlation between the scores is very high ($r = 0.98$ for cognitive skills and $r = 0.87$ for manual skills), and the pattern of selection remains qualitatively unchanged when using the CONOCER-based scores. However, the results indicate a stronger negative selection on cognitive skills and a weaker positive selection on manual skills (see Panel A of Appendix

Table C11).As we discuss in detail in the appendix, this difference between O*NET-based and CONOCER-based skill scores stems primarily from a higher specialization of U.S. agricultural occupations in use-of-tools skills. (We do not observe meaningful differences in the cognitive / manual skill intensities between O*NET-based and CONOCER-based scores for any other occupation.) This may represent a higher use of technology in the U.S. agricultural sector compared to the agricultural sector in Mexico. While it is beyond the scope of the paper to provide an in-depth analysis of the causes and consequences of these differences, it seems likely that the low use-of-tool intensity in Mexican agriculture is driven by a large supply of relatively cheap manual labor (see also Lewis (2011) for a discussion of lower tool utilization in the presence of a large supply of supplementary labor). However, these (technology-driven) differences in one particular sector do not affect our conclusions, since excluding agricultural workers from the sample leads to a selection pattern that is not sensitive to using either O*NET-based or CONOCER-based skill measures to estimate migrant selection on occupational skills (see Panel B of Appendix Table C11).

C Selection of Emigrants on Occupational Skills Within Highly Disaggregated Labor Markets

In Section IV, we document the pattern of migrant selection on occupational skills at the national level. This national-level approach connects our analysis with previous literature on migrant selection, which is almost exclusively interested in explaining migrant selection from one country to another. However, to better understand the mechanisms that lead to the observed migration pattern at the national level, it is useful to focus on more disaggregated segments of the labor market. One example will fix ideas. Cooks and waiters in Mexico are engaged in the same production process (i.e., have the same three-digit occupational code) and have roughly similar hourly wages (cook: 3.10 US-$; waiter: 2.79 US-$). However, cooks have a comparative advantage in manual skills (manual skills: 0.63; cognitive skills: 0.33) compared to waiters (manual skills: 0.68; cognitive skills: 0.59), because their job involves considerably less customer interaction. Thus, our theoretical model predicts that cooks have a higher migration propensity than waiters because they can earn relatively more from relocating their relatively high manual skills abroad. This is indeed what we observe: migration propensity of cooks is more than 50% higher than migration propensity of waiters. Apparently, such comparison provides a much stronger test of the economic mechanism underlying the Roy/Borjas model than our national-level analysis, in which we also compare migrants and non-migrants with very different backgrounds (in the extreme, professors and farmers). One may therefore expect a substantial degree of omitted variable bias when estimating the relationship between migration propensity and occupational skills at the national level.

To investigate whether the cook-vs.-waiter example also holds more generally in the Mexican population, we estimate the pattern of selection on occupational skills within narrow labor-market segments. Our analysis begins with the specification in Column 7 of Table 2 that looks within broader occupational labor markets (see also Column 1 of Table 6). This specification compares migration propensities of workers who provide roughly the same service (e.g., food services), but assumes that migration propensities of each occupational group are constant during our period of observation (2005–2014). However, year-specific shocks may differently affect workers within the same occupational group. In our above example, if the United States eases entry for Mexican cooks relative to waiters in a particular year, the estimated relationship between occupational skills and migration propensity might just occur due to this legislative change. To account for this, we interact three-digit occupation fixed effects with year fixed effects, comparing workers within the same occupational category in the same year (Column 2). The selection pattern remains almost unaffected.

Another concern is that the distribution of occupations across Mexican states is correlated with migration propensity (e.g., lower average migration costs in states close the U.S. border). We account for this possibility in Column 3 of Table 6 by defining labor markets along occupational groups, years, and state of residence. We find a similar, albeit slightly weaker, selection pattern, implying that regional economic differences partly explain the national-level results (see also Columns 5 and 6 of Table 2). One main determinant of differences in regional economic activity is a region's industry structure. Again referring to our previous example, migration propensities of cooks and waiters may be affected by the industry in which they are employed (e.g., small restaurants vs. firm canteens). In Column 4, we therefore augment our previous specification with industry fixed effects at a detailed (four-digit) level, leading to a total of 226,197 labor-market segments with more than one observation. This highly demanding specification shows a similar, and even somewhat stronger, selection pattern. This implies that the results in Column 3 (especially the weaker positive selection on manual skills) are partly due to regional differences in the availability of industries. Overall, our evidence suggests that the selection pattern holds when comparing migrants and non-migrants who provide similar services in the same industry, state, and year. These comparisons within highly disaggregated labor markets thus strongly support the conclusions from the national-level analysis.

V Selection on Earnings and Differential Labor-Market Returns

This section relates differential labor-market returns, which are the main driving force in the Roy/Borjas model, directly to migration propensity and the selection on earnings (see Kaestner and Malamud, 2014 for the same approach). We first show that at the national level both migration propensity and selection on earnings can be explained by differential returns to occupational skills (i.e., skill-specific differences in log wages). These returns outperform previously studied differential returns to "basic skills" (i.e., returns to education, age, and marital status) (Ambrosini and

Peri, 2012; Kaestner and Malamud, 2014). When focusing on highly disaggregated labor markets, two important findings emerge. First, there is no selection on earnings anymore, indicating that labor markets are very homogeneous. Second, differential returns to basic skills become negatively related to migration propensity, which is inconsistent with the Roy/Borjas model. In contrast, differential returns to occupational skills remain positively related to migration, which provides evidence that migration benefits originate from occupational choices rather than from previously studied factors such as education, age, and marital status.

A Selection on Earnings and Differential Returns at the National Level

It is well established that Mexican emigrants are negatively selected on home country earnings (see Appendix B). Our results support this finding both qualitatively and quantitatively: individuals in the top quintile of the hourly earnings distribution are about 72% less likely to migrate compared to individuals in the bottom quintile (Table 7, Column 1 of Panel B), translating into a strong negative mean selection on log hourly earnings (Column 1 of Panel A).[54]

As discussed in Kaestner and Malamud (2014), negative selection on earnings might be explained by a negative correlation between the benefits of migration and earnings (i.e., those with the highest earnings in Mexico profit the least from migration). Migration benefits are typically measured by the difference in labor-market returns to different observable characteristics between recent Mexican migrants in the United States and Mexican residents, restricting any analysis to those characteristics that can be equivalently measured in the Mexican and U.S. data. Based on the assumption that earnings reflect factors such as education, age, and family background, as well as occupational choices and the associated skills, we estimate two sets of returns: *basic returns* and *occupational returns*. Basic returns consider differential returns to years of schooling, age, and marital status (Ambrosini and Peri, 2012; Kaestner and Malamud, 2014). Occupational returns are based on differences in returns to cognitive and manual skills. In what follows, we show that negative selection on earnings is largely explained by differential returns to occupational skills rather than basic skills.

To construct differential labor-market returns, we follow Kaestner and Malamud (2014) in estimating Mincer-type regressions separately for Mexican residents in the 2000 Mexican Census and for Mexican migrants in the United States (migrated to the United States between 1990 and 2000) in the 2000 U.S. Census.[55] Appendix D.D provides details on the Census data. First, we

[54] See notes of Table 7 or Appendix D.D for the construction of hourly earnings.

[55] The results are robust to calculating differential returns for time periods closer to the sample period. First, in Appendix Tables A6 and A7, we calculate returns for recent Mexican migrants in the United States based on the 2010 U.S. ACS. Second, we check whether potential changes in the return structure over time (in particular, after the financial crisis in 2008) matter for our results. Restricting the ENOE sample to the years 2010 to 2014 and using returns that are based on the 2010 U.S. ACS (recent Mexican migrants) and the 2010 Mexican Census (Mexican residents), Appendix Table A8 implies that occupational returns—relative to basic returns—are even more important for understanding

estimate the regressions with a full set of interactions between years of schooling (five categories), age (six categories), and marital status (two categories) to predict basic returns and with a full set of interactions between cognitive skills (four categories) and manual skills (four categories) to predict occupational returns. We construct the four categories for manual and cognitive skills by splitting the occupational skill distributions at their 25th, 50th, and 75th percentiles in the 2000 Mexican Census. We also use these cutoffs to construct the same skill categories in the 2000 U.S. Census. Employing the cell approach to construct returns to skills addresses the issue that skills should be evaluated as skill bundles (Heckman and Scheinkman, 1987; Autor and Handel, 2013) and also follows common practice in the migration literature to assume perfect substitutability in production within skill cells (Borjas, 2003).[56] Second, based on the predicted earnings for Mexican residents and for Mexican migrants, we construct labor-market returns for each skill cell by subtracting the predicted log wage of the baseline category (see Appendix Figure A4) from the predicted log wage in the respective cell. Third, we calculate differential labor-market returns by cell-wise subtraction of the labor-market return for Mexican migrants from the labor-market return for Mexican residents.[57] Fourth, we merge the differential labor-market returns with the Mexican labor-force data by years of schooling category, age category, and marital status (basic returns) and by cognitive/manual skill category (occupational returns), respectively.

In line with Ambrosini and Peri (2012) and Kaestner and Malamud (2014), we observe that basic returns are a highly significant predictor of the migration decision (Column 2 of Table 7). Increasing differential basic returns by 1 unit, that is, 100 percentage points, increases migration propensity by 72% (Panel A) or 69% (Panel B) of the average migration rate, which is close to the 66% found by Kaestner and Malamud (2014, p. 86) using MxFLS data. Basic returns also explain a large part of the selection on earnings, as the coefficients on log hourly earnings (Panel A) and on all earnings quintiles (Panel B) decrease in absolute size compared to the specification without basic returns. For example, a doubling of log hourly earnings is associated with a decrease in migration propensity by only 17% (instead of 33.5%) and migration propensity drops from 72% to 38% for the highest earnings quintile vs. the lowest quintile.

However, measuring the benefits of migration by differential occupational returns shows an impact on migration propensity that is more than twice as large as the impact of differential basic

migrant selection in this period. In fact, basic returns become both statistically and economically insignificant once we account for occupational returns, while occupational returns remain sizeable and highly significant.

[56] The assumption of substitutability may hold less for basic returns (based on 60 categories) than for occupational returns (based on 16 categories). However, the relative contribution of basic returns vis-à-vis occupational returns in explaining earnings selection is very similar when basic returns are based on 18 categories only (three categories each for education and age, two for marital status).

[57] Appendix Figure A4 shows the structure of the differential returns together with confidence intervals. The figures imply that differential returns are fairly precisely estimated; in particular, they discriminate between the returns to skills of low-skilled vs. high-skilled workers. Importantly, the occupational returns clearly predict the highest positive differential returns for the low cognitive / high manual skill combination.

returns (Column 3 of Table 7). Moreover, including occupational returns reduces the coefficients on log hourly earnings and on all earnings quintiles considerably more strongly than is the case for basic returns (e.g., to -7.5% for log hourly earnings and to -21% for the highest quintile vs. the lowest quintile). In Column 4, we simultaneously include basic returns and occupational returns to assess the relative importance of each type of returns. We find the coefficient on occupational returns to be significantly larger than the respective coefficient on basic returns ($p < 0.0001$). Strikingly, the coefficient on basic returns decreases by a factor of three as compared to the specification without occupational returns, while the coefficient on occupational returns remains almost unchanged. This suggests that basic returns play only a minor role in explaining the migration pattern once we account for occupational returns.[58] Moreover, when adjusting for both return measures little selection of migrants with respect to earnings remains.

Negative selection on earnings might also be explained by a positive correlation between migration costs and earnings; that is, those with the highest migration costs are those with the highest earnings (Kaestner and Malamud, 2014). In Column 5 of Table 7, we add the travel distance to the U.S. border as a proxy for the cost of migration. In line with previous results (Fernández-Huertas Moraga, 2013; Kaestner and Malamud, 2014), accounting for migration costs leads to slightly more pronounced selection on earnings. However, it does not affect the impact of differential returns on earnings selection. In further analysis using MMP data, we also find that including different types of household assets (i.e., animal livestock holdings, land holdings, property holdings, and vehicle holdings), which may serve as indicators of household credit constraints, does not affect the selection pattern (results not shown).

In Appendix H, we address the inherent selection bias associated with these simple calculations of the differential returns to skills. We also show that our results become even stronger when using ENET data. This suggests that our returns-to-occupational-skills measures, which are based on the 2000 Mexican Census and the 2000 U.S. Census, are somewhat more appropriate for proxying the expected returns of potential Mexican migrants in the ENET data (conducted from 2000 to 2004) than in the ENOE data (conducted from 2005 onward).

B Selection on Earnings and Differential Returns Within Highly Disaggregated Labor Markets

To shed more light on the role of differential labor-market returns for the migration decision and to rule out some endogeneity concerns, we again focus on narrow labor markets. We have shown in the previous section that those with the lowest earnings in Mexico benefit the most from migration. In line with the Roy/Borjas model, our analysis also suggested that differential returns to skills are

[58]Using two-way clustered standard errors at the level of our skill cells (16 categories for occupational skills and 60 categories for basic skills) to account for the correlation within skill cells, basic returns even turn insignificant when jointly included with occupational returns.

causing these benefits and therefore determine migration. Whether this is indeed the case depends strongly on the assumption that no other confounding factors correlate with differential returns to skills, earnings, and migration propensity. This assumption is unlikely to hold. For example, individuals who have low earnings in Mexico and work in high-manual low-cognitive jobs might just want to escape poverty and therefore migrate to the United States. This group of workers may also have a higher migration propensity because they live in regions that are associated with lower migration costs (e.g., regions closer to the U.S. border). It may also be that this worker group is predominantly employed in industries that are on a downward economic trend. Any of these reasons could have led to our previous results without migrants having actually reacted to differential labor-market returns to their skills.

In Table 8, we replicate the specifications from Table 7 within narrow labor markets; that is, we compare migrants and non-migrants within the same labor-market segment defined by the intersection of occupation (three-digit level), industry (four-digit level), year, and residence state (see Column 4 of Table 6). Referring to our previous example, this analysis essentially answers the question whether cooks (having a comparative advantage in manual skills) and waiters (having a comparative advantage in cognitive skills) react differently to differential labor-market returns to skills. Our first striking result is that within narrow labor markets migrants are *not* selected on mean earnings (Panel A of Table 8), and there is little, if any, selection along the earnings distribution (Panel B of Table 8). This means that a worker's migration propensity is not anymore related to his level of earnings when focusing on very homogeneous segments of the labor market, indicating a much higher degree of similarity between migrants and non-migrants than in the national-level analysis. This provides an excellent setup for testing the Roy/Borjas model because migrants and non-migrants have similar opportunity costs of migration (i.e., foregone earnings in Mexico) and similar potential to bear direct migration costs (e.g., due to access to credit or availability of household assets). Thus, a positive relationship between differential returns to skills and migration reflects perceived economic benefits in the United States.

The results in Columns 2 to 5 of Table 8 show that differential returns to occupational skills remain to be positively related to migration propensity within narrow labor markets. The respective coefficients are statistically significant and still twice as large as the coefficients on differential returns to basic skills at the *national level* (comparing Columns 4 and 5 of Tables 7 and 8). In contrast, the coefficients on differential returns to basic skills, which are positively related to migration at the national level, become significantly negative within narrow labor markets (not significant when using two-way clustered standard errors). Given that returns to education are higher in Mexico than in the United States (Chiquiar and Hanson, 2005; Fernández-Huertas Moraga, 2011), this result follows from substantial positive selection on education in these narrow labor-market segments (see Column 4 of Table 6).

Our results show that economic benefits of migration measured by returns to occupational skills yield predictions that are consistent with the Roy/Borjas model, even when comparing migrants and non-migrants with similar average earnings in Mexico. This analysis also rejects that previously studied returns to basic socio-economic characteristics (i.e., education, age, marital status) are regarded as economic benefits by Mexican migrants. In fact, Mexicans move to the United States despite getting higher rewards to their basic skills in Mexico than abroad.

VI Discussion

Our paper provides evidence that Mexican immigrants in the United States are positively selected on their manual skills and are negatively selected on their cognitive skills. This selection pattern is consistent with migration benefits being an important driver of migration because labor-market returns to manual (cognitive) skills for Mexicans are higher (lower) in the United States than in Mexico. Since a causal interpretation of our results is clearly difficult without exogenous variation in returns to skills, these results should be regarded as descriptive evidence on the role of occupational skills for migrant selection and on the importance of returns in explaining the selection pattern. The descriptive nature of our analysis warrants a discussion of plausible alternative explanations of the selection pattern. We also discuss how our work relates to previous evidence on international migrant selection.

A Alternative Explanations for the Selection Pattern

Immigration Policies

One may be worried that many opportunities for legal migration to the United States are closely connected to specific occupations, which are intensive in manual skills rather than in cognitive skills (e.g., H-2A and H-2B visas for temporary and seasonal work). If so, our selection results might merely be a by-product of the available set of opportunities for legal migration. While we are not able to fully disentangle selection due to monetary benefits from selection that is due to immigration policies (as we are lacking exogenous variation in returns to skills), several pieces of evidence, outlined below, make us confident that the selection pattern is not just a by-product of immigration policies.

Usually, migration policies in most developed countries favor high-skilled immigration over low-skilled immigration. In contrast, however, the United States has established legal avenues for high-skilled and low-skilled Mexican migration. More specifically, due to the availability of various visa categories, both high-manual/low-cognitive and low-manual/high-cognitive Mexicans can legally enter the United States. First, for permanent migration, 90% of Mexican migrants are admitted under family reunification provisions (see, e.g., Chiquiar and Hanson, 2005), which are not tied to any specific occupation or education level. Given the large network of Mexicans in the United States, it is not surprising that a majority of Mexican migrants are using this opportunity to enter the United States (even if they would also be eligible for other visa categories). Over the period from 2000 to 2015, a total of 997,800 immigrant visas have been issued to Mexican nationals; 59% have been granted to immediate relatives, such as spouses, children, or parents (immediate-relative visas are without caps) and further 40%have been granted to specific, more distant, family members (such family-preference visas are currently capped at a total number of 480,000 per year) (U.S. Department of State, 2020b).[59]

Second, there are also legal avenues for temporary migration (which may eventually lead to permanent migration) that are open to Mexican workers in a wide array of occupations. On the one hand, high-educated Mexicans can migrate temporarily via H-1B visas. For example, nonimmigrant visa statistics by the U.S. Department of State (2020a) over the period from 2000 to 2015 show that 45,216 H-1B visas (2.1% of all H-1B visas) have been issued to Mexican nationals. This makes Mexico the seventh largest receiver of H-1B visas (followed by countries such as France (36,036 H-1B visas) and Germany (32,612 H-1B visas)). However, for most high-educated Mexicans, it is easier to migrate via a TN visa because these visas are granted only to Mexican and Canadian nationals due to the NAFTA agreements without any caps. Over the period from 2000 to 2015, Mexican nationals received 70,904 TN visas (99% of all TN visas). H-1B and TN visas are initially granted for the duration of three years and can usually be renewed. On the other hand, lower-educated Mexicans can migrate via H-2A (agricultural workers) and H-2B (non-agricultural occupations, mainly landscaping and groundskeeping, forestry, amusement/recreation, hospitality, meat/fish processing, construction, and restaurant services). The nonimmigrant visa statistics by the U.S. Department of State (2020a) over the period from 2000 to 2015 show that 93% of all H-2A visas (789,243 visas) and 67% of all H-2B visas (681,757 visas) have been granted to Mexican nationals. The duration of these visas is usually much shorter than the duration of H-1B and TN visas (sometimes only for the harvest season).

While the visa statistics highlight that migration is possible for Mexicans over the whole distribution of occupational skills, the uptake of visa opportunities is endogenous and—as we argue in this paper—at least partly due to the structure of differential returns; that is, the less frequent use of H-1B and TN visas as compared to H-2A and H-2B visas may simply reflect that the relatively low returns to cognitive skills for Mexicans in the United States render these visa programs less attractive. In general, the pattern in visa issuance is also consistent with the explanation that visas

[59]Note that visas issued under the immediate-relative category reduce the available number of family-preference visas. However, at least 226,000 visas must be allocated through family-preference visas to avoid that family-related visas are just issued to immediate relatives. In fact, migration via this channel could be much larger if there were no caps. Currently, Mexico is at the top of the waiting list for family-preference visas with 1,206,562 applicants (U.S. Department of State, 2019).

are more difficult to obtain for high-cognitive workers (e.g., because of more complicated paperwork and more regulations) than for low-cognitive workers. However, the common perception in the literature seems to be that migration costs are decreasing with education (e.g., Chiquiar and Hanson, 2005), favoring the migration of high-educated migrants (who are more likely to work in high-cognitive, low-manual jobs). Potential reasons for migration costs decreasing with education are that higher-educated individuals are better able to handle the paperwork for visa admissions, can more easily bear the direct monetary costs of the visa process, and are less credit constrained.

Still, the legal opportunities to migrate likely differ between different types of Mexican workers in a way unobserved to us, affecting the expected migration benefits and thus the selection pattern. However, several additional analyses suggest that immigration policies are not a major driver of our results (see Appendix I for details). For instance, the selection pattern is stable over time, that is, across very different immigration policy and visa regimes (see Appendix I.A). Results are also robust to dropping temporary and seasonal migrants (who often use H-2A and H-2B visas to work in high-manual/low-cognitive occupations) or agricultural workers (i.e., the only occupational group that has its own visa program) (see Appendix I.B). The observed selection neither follows a seasonal pattern, so it is not driven by, for instance, the harvest season. Furthermore, the selection pattern remains qualitatively unchanged when workers are likely to face the same legal migration opportunities; that is, when we compare workers within the same three-digit occupation (see Section IV.C) or within the same education category (see Section IV.A).

Legal Status

According to the latest estimate from the Pew Research Center, about half of Mexican emigration is unauthorized, meaning illegal or undocumented (Gonzalez-Barrera and Krogstad, 2017). One worry is that the observed selection pattern of Mexican migrants is affected by undocumented migrants who fear to be deported back to Mexico. In particular, the risk of short-term migration illegal migrants face (e.g., due to deportation) can affect their subjective returns expectations. If the cross-border transferability of cognitive skills was more limited than the transferability of manual skills, this could give rise to the observed selection pattern even if the true return to both skills would be the same in Mexico and the United States. While we have already discussed in the previous paragraph that dropping temporary migrants from the sample does not affect the results, a further comprehensive analysis in Appendix I.C suggests that our results are robust to accounting for legal migration status. However, since we cannot entirely rule out that expected returns to cognitive and manual skills are a function of the migrant's documentation status, our selection results may partly be explained by (the lack of) legal migration opportunities.

Endogenous Skill Formation

Another concern is reverse causality from immigration decision to occupational choices and acquired skills. Such endogenous skill formation would lead to an upward bias in the estimated coefficients on both cognitive skills and manual skills if future migrants purposefully chose high-manual/low-cognitive jobs in Mexico, as these provide the highest perceived returns to migration. There is also the possibility of imperfect job-worker matching, for instance, because a negative labor-market shock forces workers to enter a less desirable occupation and pushes them to migrate. In Appendix J, we show that endogenous skill formation is unlikely to be driving our results.

B Relation to Previous Results on International Migration

There is an ongoing discussion in the literature about whether differential returns (i.e., skill-specific differences in *log* wages) or differential wage levels (i.e., skill-specific differences in *absolute* wages) are more suitable for explaining migrant selection. For example, Grogger and Hanson (2011) find that differential wage levels and not differential returns can predict migrant selection on education in a cross-country setting. In contrast, Appendix Table A9 shows that wage levels are not positively associated with Mexican immigration in the United States and are not related to selection on earnings. This confirms the results in Kaestner and Malamud (2014), who also show that wage levels do not predict migration behavior between both countries.

There are at least two potential reasons why we observe this inconsistency in the literature. First, skill-specific migration costs are more important in the cross-country analysis than they are in the Mexico-U.S. case. For example, Belot and Hatton (2012), using a very similar setup as Grogger and Hanson (2011), find that wage levels cannot predict migrant selection on education when they account for poverty constraints as a measure of skill-specific migration costs. Another potentially omitted variable is presented by Krieger et al. (2018), who show that international migrant selection on education is sensitive to the long-term relatedness between countries in the sense that low-educated migrants consider moving to a culturally more distant destination to a lesser extent than high-educated migrants do. This illustrates that cross-country comparisons may suffer from omitted variable bias. Second, because cross-country studies usually focus on education to measure the skills of migrants, they may miss the importance of (returns to) occupational skills for the migration decision. For example, Figure 4 shows that differential returns to occupational skills between the United States and Mexico are positively associated with migration propensity within each education category. The estimates imply the strongest association between migration propensity and occupational returns for individuals with intermediate levels of education. This is consistent with the finding of overall intermediate selection on education between Mexico and the United States when studying selection along the education distribution (see Appendix Table A1 and, e.g., Fernández-Huertas Moraga, 2011; Kaestner and Malamud, 2014).

Moreover, our study suggests that education does not appear to have much explanatory power for predicting migration over and above its impact on occupational choices (specifically when considering that differential returns on occupational skills clearly outperform differential returns on basic skills, which include education, in predicting migration behavior). This finding implies that if selection on different skill dimensions yields opposing patterns, these are difficult to interpret if selection on one skill dimension (e.g., education) is correlated with selection on another potentially more important skill dimension (e.g., occupational skills) (see Borjas, 1991; Dustmann and Glitz, 2011, for a theoretical discussion). Supporting evidence for this idea comes from Parey et al. (2017). Using the case of German university graduates migrating abroad, they find that more able graduates—measured by predicted wages based on a very rich set of individual covariates—move to less equal countries and less able graduates move to more equal countries relative to Germany. This selection pattern confirms the relevance of the Roy-Borjas model for the selection of high-skilled migrants, for whom migration costs should be less important than for low-skilled migrants. However, they also show that there is positive selection on university grades (as a measure for educational attainment) for all migrant groups. This implies that cross-country studies looking at educational selectivity may miss other dimensions of skills that are important for migration decisions. Thus, examining the role of occupational skills in the migration decisions may also inform the literature on cross-country migrant selection.

VII Conclusions

In this paper, we provide the first evidence how migrants and non-migrants differ in their occupational choices and acquired skills. We develop measures of workers' occupational skills using data from a representative Mexican survey of job tasks—similar to the U.S. O*NET—and combine these measures with detailed longitudinal individual-level data from a Mexican labor-force survey. We show that Mexican emigrants to the United States are positively selected on manual skills and negatively selected on cognitive skills, consistent with a two-dimensional Roy/Borjas model with related skills. The selection pattern also holds within narrowly defined labor markets that account for potential confounding factors at the level of years, states, industries, and occupations. A similar selection pattern prevails when we use other sources of Mexican data that cover additional time periods and include workers' full occupational histories, permanent migrants, return migrants, and migrating households.

Our results not only inform politicians on both sides of the border about migrants' knowledge and capabilities directly relevant in the labor market, they also shed new light on how to interpret previous evidence from the migrant selection literature. Our results suggest that many of the selection mechanisms studied in previous papers materialize almost entirely through the selection on occupational skills. For instance, the negative selection on education can be explained by the fact that better education enables workers to enter occupations with a higher cognitive skill content. Although it is not surprising that education and type of job are related, we show that education plays almost no role in migrant selection and the assessment of migration benefits over and above its effect on occupational choice.

We also show that occupational skills are important for understanding the selection of migrants with respect to earnings. When adjusting for differential labor-market returns to occupational skills between the United States and Mexico, the selection on earnings vanishes almost completely. The change in the pattern of selection after this adjustment implies that differential returns to occupational skills are an important determinant of migration and the primary explanation of the negative selection of migrants with respect to earnings. It also suggests that occupational skills provide almost the same information as earnings in explaining migrant selection, although earnings are a much more comprehensive measure of the productive capacity of migrants encompassing inputs such as schooling, family background, local labor-market conditions, and peer effects.

However, due to the descriptive nature of our analysis, a causal interpretation of the relationship between differential returns to occupational skills and migration behavior is clearly difficult. Exploiting exogenous variation in returns to skills would therefore be an important building block toward better understanding migration behavior. Another promising avenue for further research would be the collection of data on job tasks in other emigration countries to study the selection on occupational skills for a wide range of migration flows.

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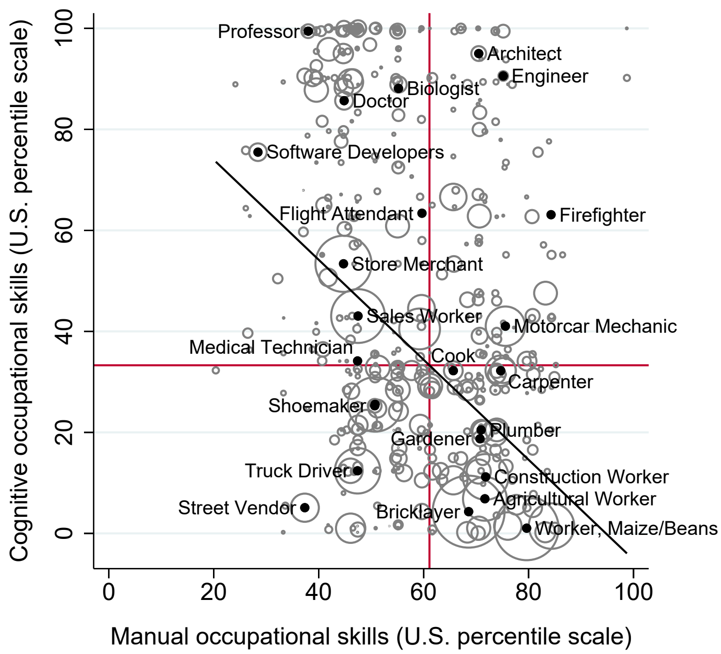
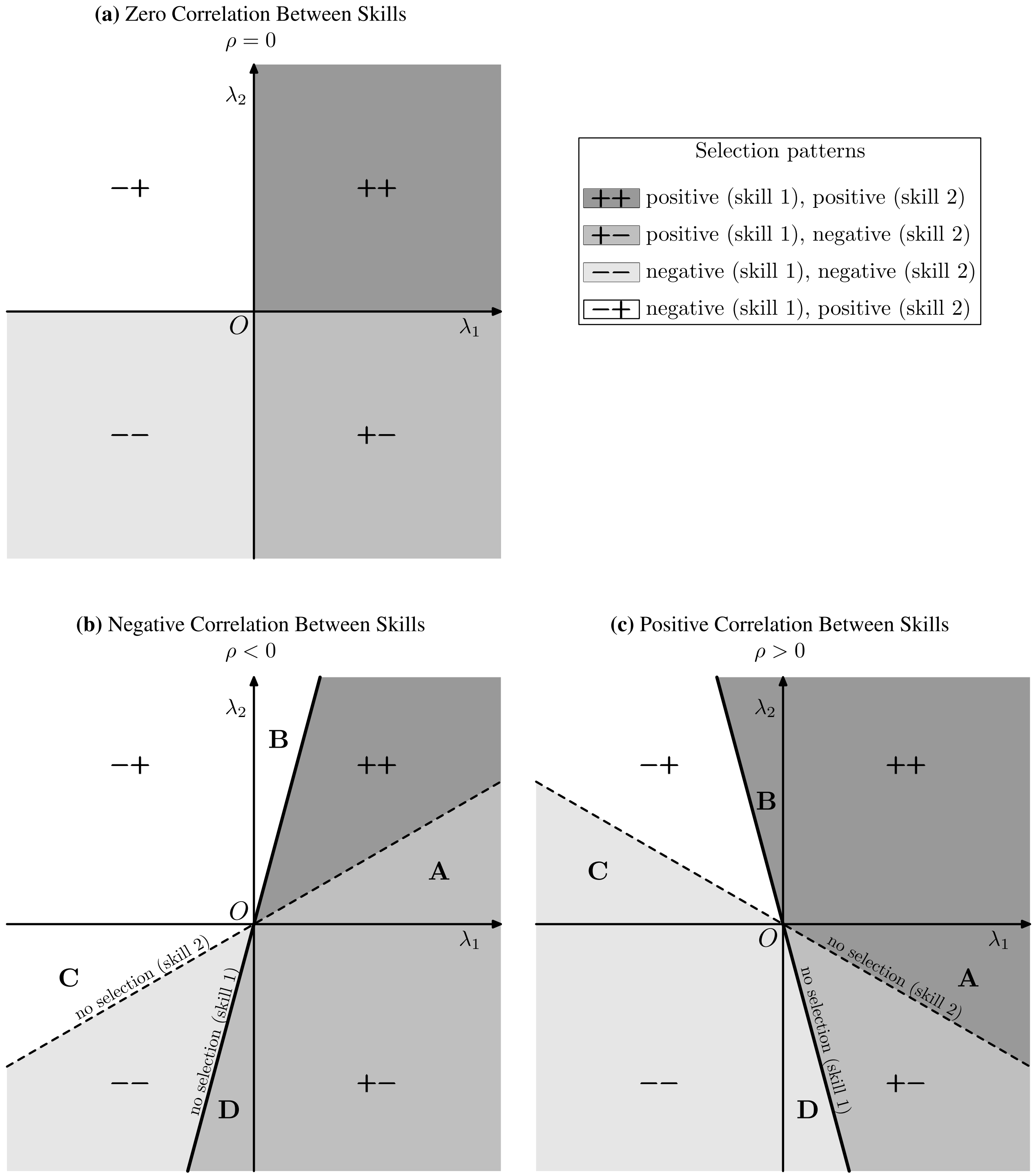
Figures and Tables

Figure 1: Cognitive and Manual Occupational Skills in the Mexican Population



Notes: Figure plots cognitive and manual occupational skills in the Mexican population, measured in U.S. 2010 percentile ranks and weighted by the number of observations in the 2010 Mexican Census. Sample restricted to male Mexicans aged 16–65. Occupations whose titles are shown are represented by filled dots; the size of the hollow circles around the filled dots is proportional to the number of Mexicans working in the occupation in the 2010 Mexican Census. Regression line (black) is weighted by numbers of observations. Red lines show weighted averages of cognitive and manual occupational skills. The population-weighted correlation between the skills is $\rho = -0.46$ and the unweighted (i.e., occupation-level) correlation is $\rho = -0.18$. *Data sources:* 2010 Mexican Census, Mexican CONOCER, and U.S. O*NET.

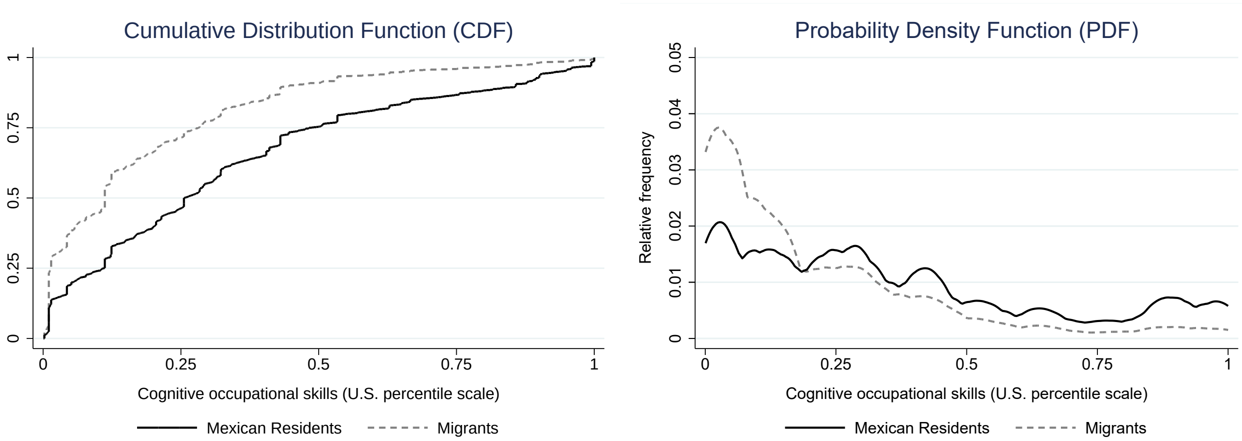
Figure 2: Selection Patterns for Different Correlations Between Skill 1 and Skill 2



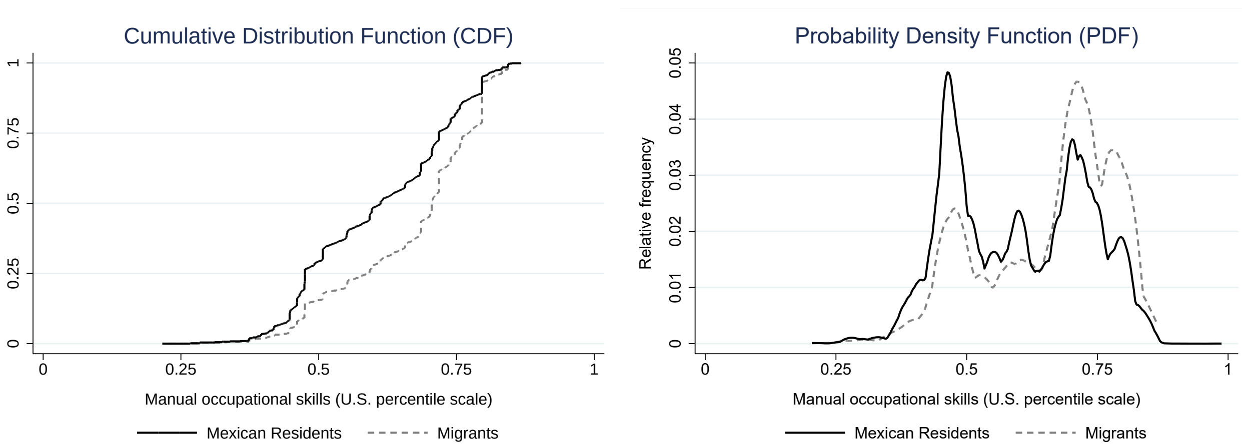
Notes: Figure shows the predictions of the two-dimensional Roy/Borjas model (Section III.A) when skill 1 and skill 2 are uncorrelated (Figure 2(a)), negatively correlated (Figure 2(b)), or positively correlated (Figure 2(c)). Regions are defined as follows: "$++$" for positive selection on both skills; "$+-$" for positive selection on skill 1 and negative selection on skill 2; "$--$" for negative selection on both skills; and "$-+$" for negative selection on skill 1 and positive selection on skill 2. See text for definitions of the areas A, B, C, and D in Figures 2(b) and 2(c). The solid line corresponds to the knife-edge case of no selection on skill 1 when (λ_1, λ_2) lie on the line $\lambda_1 + \beta_{2,1}\lambda_2 = 0$, which divides the space into positive and negative selection half-planes. The dashed line corresponds to no selection on skill 2. The slope of the dashed line is always smaller than the slope of the solid line.

Figure 3: Emigrant Selection on Occupational Skills

(a) Cognitive Occupational Skills

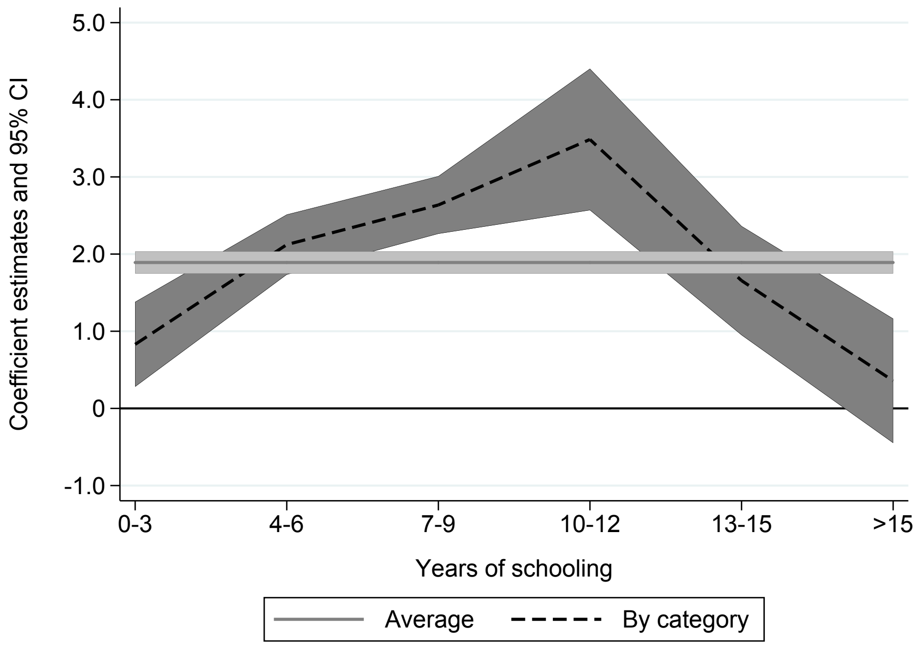


(b) Manual Occupational Skills



Notes: Figures show cumulative distribution functions (left panels) and probability density functions (right panels) of cognitive skills (Figure 3(a)) and manual skills (Figure 3(b)) by migration status. Sample consists of male Mexicans aged 16–65. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Kolmogorov-Smirnov tests and tests suggested by Borjas et al. (2019) (see Appendix Figure A2) on stochastic dominance indicate that differences between cumulative distribution functions are significant at the 1% level. $N = 8,701$ Mexican migrants in the United States and $N = 2,950,827$ Mexican residents. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Figure 4: Migration Propensity and Differential Returns to Occupational Skills: Results by Education Category



Notes: Figure shows coefficients and 95% confidence intervals, which are obtained from regressing the migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by the sample-specific quarterly migrant share on Δ occupational returns. All regressions contain quarter-by-year fixed effects. Δ occupational returns indicate differential returns for occupational skills between the United States and Mexico. They are constructed by calculating differential labor-market returns for recent Mexican migrants in the United States (immigrated 10 years prior to the survey with an age of 16 years or more at time of arrival) and Mexican residents in the 2000 Mexican Census. Predicted returns are based on a Mincer-type regression with a full set of interactions between cognitive skills (four categories) and manual skills (four categories). Cutoffs for the occupational skill distribution are based on the Mexican population in 2000. *Average* includes all observations across all years-of-schooling categories. *By category* runs the regressions within each of the six education categories indicated on the horizontal axis, using category-specific Δ occupational returns. Observations are weighted by sampling weights. Robust standard errors are clustered at the household level. The correlation between average Δ occupational returns and the education-specific Δ occupational returns ranges between $r = 0.45$ and $r = 0.78$. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

Table 1: Skill Content of Mexican Occupations

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Panel A: Top six occupations									
Cognitive occupational skills					Manual occupational skills				
Occupation	Cognitive skills		Manual skills		Occupation	Manual skills		Cognitive skills	
	Score	Percentile	Score	Percentile		Score	Percentile	Score	Percentile
Managers/Coordinators	2.52	1.00	-0.47	0.46	Operators of agricultural machinery	1.76	0.85	-2.73	0.01
Municipal authorities	2.39	1.00	-0.31	0.48	Farm managers and foremen	1.75	0.85	-0.86	0.31
Hotel managers	2.38	1.00	-0.32	0.48	Support workers in agriculture	1.62	0.84	-2.59	0.01
Specialists in HR and management systems	2.31	1.00	-0.23	0.51	Mining workers	1.57	0.84	0.07	0.43
Secondary school teachers	2.28	1.00	-0.20	0.53	Loggers	1.47	0.84	-1.95	0.12
Professors	2.09	0.99	-1.09	0.38	Supervisors of industrial machinery operators	1.41	0.83	0.29	0.48
Panel B: Bottom six occupations									
Cognitive occupational skills					Manual occupational skills				
Occupation	Cognitive skills		Manual skills		Occupation	Manual skills		Cognitive skills	
	Score	Percentile	Score	Percentile		Score	Percentile	Score	Percentile
Log splitters	-3.85	0.00	0.35	0.70	Software developers	-1.38	0.28	1.12	0.75
Workers in cattle breeding	-3.30	0.00	0.31	0.68	Photographers	-1.30	0.32	0.31	0.50
Workers in other crops	-3.29	0.00	1.40	0.83	Fiber weavers	-1.24	0.33	-1.08	0.28
Garbage collectors	-3.11	0.01	-0.37	0.47	Auxiliary social scientists/humanists	-1.18	0.37	0.55	0.60
Workers in maize/beans	-2.86	0.01	0.97	0.80	Aids in administration and sales	-1.14	0.37	1.66	0.91
Charcoal producers	-2.81	0.01	-0.49	0.47	Street vendors	-1.13	0.37	-2.29	0.05

Notes: Table shows the ranking of the top six and bottom six occupations according to their cognitive and manual occupational skill score. Ranking of occupations is based on the empirical distribution in the Mexican Census 2010. Sample is restricted to Mexican males aged 16–65. Only occupations with more than 1,500 observations in the census are considered. Percentiles give the position in the U.S. 2010 occupational skill distribution. See text for details. *Data sources:* Mexican CONOCER, U.S. O*NET, and 2010 Mexican Census.

Table 2: Emigrant Selection on Occupational Skills: Results at National Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: migration propensity to the U.S.							
Cognitive skills	–0.126***	–0.160***		–0.164***	–0.161***	–0.132***	–0.111***
	(0.006)	(0.007)		(0.009)	(0.009)	(0.009)	(0.015)
Manual skills	0.205***	0.177***		0.182***	0.168***	0.126***	0.065**
	(0.015)	(0.014)		(0.014)	(0.014)	(0.015)	(0.028)
Cognitive skills × manual skills		–0.076***		–0.079***	–0.074***	–0.050***	–0.037***
		(0.005)		(0.005)	(0.005)	(0.005)	(0.008)
Years of schooling			–0.072***	0.010*	0.016***	0.035***	0.017***
			(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Age			–0.037***	–0.032***	–0.030***	–0.029***	–0.032***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed Effects							
Birth-by-residence state [1,239]					x		
Municipality [1,499]						x	
Occupation [156]							x

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Average yearly (quarterly) migration rate is equal to 1.35% (0.34%). Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Skill measures are demeaned and scaled by 10. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,959,528$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table 3: Average Migration Propensity by Skill Category

	(1)	(2)	(3)
Cognitive skills	Manual skills		
	Low	High	$\beta_{\text{manual skills}}$
Low	0.722	1.634	0.436
High	0.453	0.592	0.041
$\beta_{\text{cognitive skills}}$	–0.057	–0.264	

Notes: Table shows average migration propensities when splitting the sample at median occupational skills. Observations are weighted by sampling weights. $N = 2,959,528$. Median cutoffs for the occupational skill distribution are based on the Mexican population in 2000 and the sample is restricted to Mexican-born males aged 16–65 who are not in school and work between 20 and 84 hours per week. For manual skills, the low-category ranges between 0.203 and 0.577 and the high-category between 0.577 and 0.987 of the U.S. manual skill distribution. For cognitive skills, the low-category ranges between 0.000 and 0.314 and the high-category ranges between 0.314 and 1.000 of the U.S. cognitive skill distribution. $\beta_{\text{cognitive skills}}$ report the linear coefficient on cognitive skills in a regression of migration propensity on cognitive skills and quarter-by-year fixed effects within the manual skill category indicated in the column header. $\beta_{\text{manual skills}}$ report the linear coefficient on manual skills in a regression of migration propensity on manual skills and quarter-by-year fixed effects within the cognitive skill category indicated in the first column. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table 4: Emigrant Selection on Occupational Skills: Results by Years of Schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: migration propensity to the U.S.							
	Baseline	0–3 years	4–6 years	7–9 years	10–12 years	13–15 years	> 15 years
Cognitive skills	–0.164***	–0.088***	–0.102***	–0.201***	–0.219***	–0.213***	–0.115***
	(0.009)	(0.028)	(0.021)	(0.013)	(0.019)	(0.059)	(0.042)
Manual skills	0.182***	0.202***	0.114***	0.134***	0.142***	0.231**	0.104
	(0.014)	(0.054)	(0.034)	(0.020)	(0.037)	(0.118)	(0.129)
Cognitive skills × manual skills	–0.079***	–0.004	–0.070***	–0.126***	–0.087***	–0.107**	–0.027
	(0.005)	(0.020)	(0.014)	(0.010)	(0.014)	(0.042)	(0.028)
Years of schooling	0.010*	0.181***	0.043	0.060	0.127**	–0.080	0.043
	(0.005)	(0.039)	(0.052)	(0.055)	(0.062)	(0.122)	(0.076)
Age	–0.032***	–0.030***	–0.035***	–0.027***	–0.024***	–0.024***	–0.047***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.003)	(0.007)	(0.008)
Observations	2,959,528	300,246	579,752	859,959	625,085	139,969	454,517
Average migration rate (in %)	1.35	1.31	1.87	1.68	1.04	0.62	0.47

Notes: Sample includes Mexican males aged 16–65 who meet the years-of-schooling restriction specified in the column header (*Baseline:* all years of schooling; see Column 4 of Table 2). Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by sample-specific quarterly migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four quarters prior to migration. Skill measures are demeaned and scaled by 10. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table 5: Emigrant Selection on Occupational Skills: A Closer Look at Cognitive Skills

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: migration propensity to the U.S.						
Cognitive skills	–0.127***		–0.097***			
	(0.008)		(0.009)			
Communication skills		–0.181***	–0.082***	0.015	–0.068***	0.010
		(0.014)	(0.017)	(0.022)	(0.017)	(0.022)
Cognitive skills: interpersonal				–0.163***		–0.113***
				(0.014)		(0.020)
Cognitive skills: intrapersonal					–0.113***	–0.055***
					(0.010)	(0.014)
Manual skills	0.210***	0.197***	0.187***	0.207***	0.175***	0.193***
	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Years of schooling	0.009*	–0.016***	0.007	–0.001	0.009*	0.007
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Age	–0.031***	–0.034***	–0.032***	–0.031***	–0.031***	–0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. *Communication skills* use the CONOCER item of *verbal communication*. *Cognitive skills: interpersonal* are based on items that express the personality and the social skills of an individual. *Cognitive skills: intrapersonal* are based on items that express the character and the self-management skills of an individual. See Appendix C.C for details on the construction of communication, interpersonal, and intrapersonal skills. Skill measures are demeaned and scaled by 10. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,959,528$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table 6: Emigrant Selection on Occupational Skills: Results Within Narrow Labor Markets

	(1)	(2)	(3)	(4)
Dependent variable: migration propensity to the U.S.				
	Labor market specification			
	Occupation (156)	× year (10)	× state (32)	× industry (182)
Cognitive skills	–0.111***	–0.108***	–0.079***	–0.088***
	(0.015)	(0.015)	(0.016)	(0.020)
Manual skills	0.065**	0.067**	0.057**	0.084**
	(0.028)	(0.028)	(0.029)	(0.036)
Cognitive skills × manual skills	–0.037***	–0.036***	–0.027***	–0.026**
	(0.008)	(0.008)	(0.008)	(0.011)
Years of schooling	0.017***	0.017***	0.027***	0.031***
	(0.005)	(0.005)	(0.006)	(0.007)
Age	–0.032***	–0.032***	–0.031***	–0.034***
	(0.001)	(0.001)	(0.001)	(0.002)
Labor-market segments	156	1,467	39,108	226,197

Notes: See Table 2 for sample restrictions and further variable definitions. Column 1 replicates specification in Column 7 of Table 2. Numbers in parentheses in the column header report the number of categories of the indicated variable. Numbers in the bottom of each column report the number of labor-market segments with more than one observation. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,959,528$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table 7: Selection on Earnings and Differential Returns: Results at National Level

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.335***	–0.170***	–0.075***	–0.038	–0.050
	(0.026)	(0.031)	(0.029)	(0.031)	(0.032)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.719***		0.246***	0.242***
		(0.056)		(0.061)	(0.061)
Δ occupational returns$^{US,2000}_{MEX,2000}$			1.611***	1.493***	1.497***
			(0.091)	(0.099)	(0.099)
Travel distance to US border					–0.008***
					(0.003)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	–0.044	–0.002	0.046	0.053	0.036
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
3rd quintile	–0.284***	–0.209***	–0.124*	–0.111	–0.134*
	(0.068)	(0.068)	(0.068)	(0.068)	(0.069)
4th quintile	–0.491***	–0.350***	–0.218***	–0.192***	–0.216***
	(0.064)	(0.065)	(0.065)	(0.066)	(0.066)
5th quintile	–0.715***	–0.383***	–0.209***	–0.139**	–0.162**
	(0.059)	(0.066)	(0.064)	(0.068)	(0.069)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.688***		0.215***	0.215***
		(0.056)		(0.061)	(0.061)
Δ occupational returns$^{US,2000}_{MEX,2000}$			1.560***	1.457***	1.463***
			(0.090)	(0.098)	(0.098)
Travel distance to US border					–0.009***
					(0.003)

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. The construction of hourly earnings in Panel A follows Fernández-Huertas Moraga (2011). Hourly earnings are obtained by dividing monthly earnings by 4.5 $\times$ hours worked per week. Earnings quintiles in Panel B depend on hourly earnings. Earnings observations are dropped for persons who are unemployed, not in the labor force, not working in Mexico, and who work less than 20 or more than 84 hours per week. The top and bottom 0.5% of earnings observations are dropped (Chiquiar and Hanson, 2005). Earnings are denoted in constant 2010 U.S. dollars and adjusted for PPP. Δ *returns* indicate differential returns (i.e., skill-specific differences in log wages) for observable skills between the United States and Mexico following Kaestner and Malamud (2014). Returns are constructed by calculating differential labor-market returns for recent Mexican migrants in the United States (immigrated 10 years prior to the survey with an age of 16 years or more at time of arrival) and Mexican residents in the Mexican Census 2000. *Basic returns* are predicted from a Mincer-type regression with a full set of interactions between age (six categories), education (five categories), and marital status (two categories). *Occupational returns* are predicted from a Mincer-type regression with a full set of interactions between cognitive skills (four categories) and manual skills (four categories). Cutoffs for the occupational skill distribution are based on the Mexican population in 2000. *Travel distance to US border* is the travel distance in hours to the closest border checkpoint. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,950,951$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

Table 8: Selection on Earnings and Differential Returns: Results Within Narrow Labor Markets

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.018	–0.033	–0.012	–0.028	–0.030
	(0.043)	(0.044)	(0.043)	(0.044)	(0.044)
Δ basic returns$^{US,2000}_{MEX,2000}$		–0.207**		–0.226**	–0.225**
		(0.092)		(0.093)	(0.093)
Δ occupational returns$^{US,2000}_{MEX,2000}$			0.426**	0.451**	0.449**
			(0.180)	(0.181)	(0.181)
Travel distance to US border					–0.037
					(0.026)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	0.021	0.016	0.023	0.017	0.016
	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)
3rd quintile	–0.088	–0.098	–0.085	–0.096	–0.098
	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)
4th quintile	–0.141	–0.159*	–0.135	–0.155*	–0.157*
	(0.086)	(0.086)	(0.086)	(0.086)	(0.087)
5th quintile	–0.155*	–0.190**	–0.146*	–0.184**	–0.187**
	(0.086)	(0.088)	(0.086)	(0.088)	(0.088)
Δ basic returns$^{US,2000}_{MEX,2000}$		–0.234**		–0.253***	–0.252***
		(0.093)		(0.093)	(0.093)
Δ occupational returns$^{US,2000}_{MEX,2000}$			0.416**	0.445**	0.443**
			(0.180)	(0.181)	(0.181)
Travel distance to US border					–0.037
					(0.026)

Notes: Table shows results analogous to those in Table 7 within 226,197 labor-market segments at the occupation × year × state × industry level (see Column 4 of Table 6). See Table 7 for sample restrictions and further variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,950,951$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

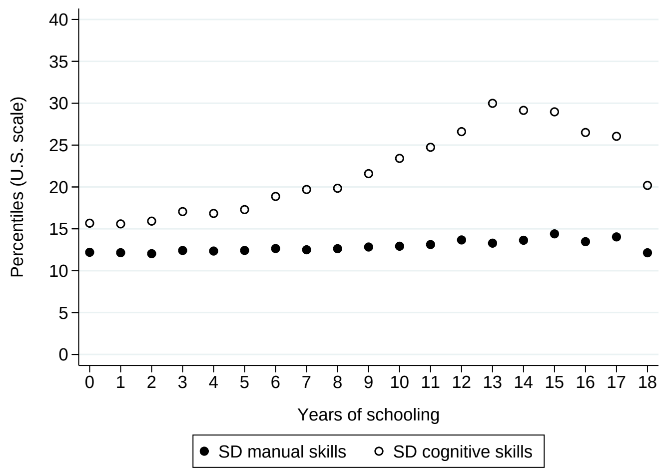
Online Appendices: Not for Publication

This is the online appendix for the paper "International Emigrant Selection on Occupational Skills" by Alexander Patt, Jens Ruhose, Simon Wiederhold, and Miguel Flores.

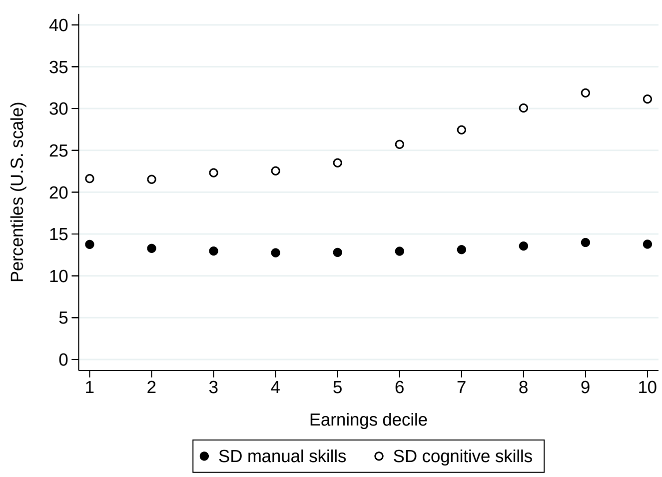
A Further Results

Figure A1: Variation in Occupational Skills Along Other Dimensions of Labor-Market Skill

(a) Years-of-Schooling Distribution



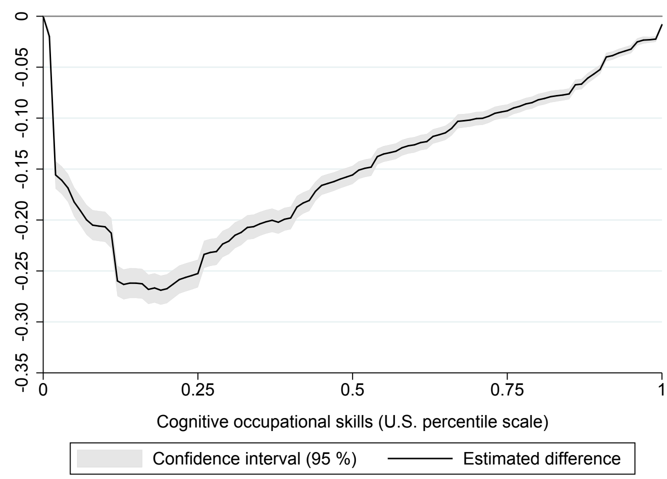
(b) Earnings Distribution



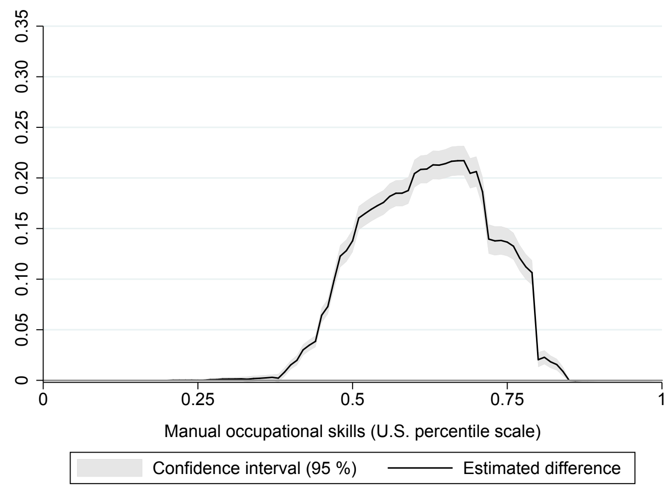
Notes: Figure plots the standard deviations of cognitive skills and manual skills (each expressed as percentile ranks in the U.S. skill distribution) within each year-of-schooling category (Figure A1(a)) and within each earnings decile (Figure A1(b)). Observations are weighted by sampling weights in the 2010 Mexican Census. In Figure A1(a), sample is restricted to male Mexicans aged 16–65; in Figure A1(b), sample is further restricted to those individuals who are not in school and work between 20 and 84 hours per week. Earnings deciles are based on hourly earnings, constructed by dividing monthly earnings by 4.5 $\times$ hours worked per week. The largest and smallest 0.5% of hourly earnings are dropped (Chiquiar and Hanson, 2005; Fernández-Huertas Moraga, 2011). Figures look very similar when using data from the 2000 Mexican Census (not shown). *Data sources:* 2010 Mexican Census, Mexican CONOCER, and U.S. O*NET.

Figure A2: Difference in CDFs of Occupational Skills between Migrants and Mexican Residents

(a) Cognitive Occupational Skills



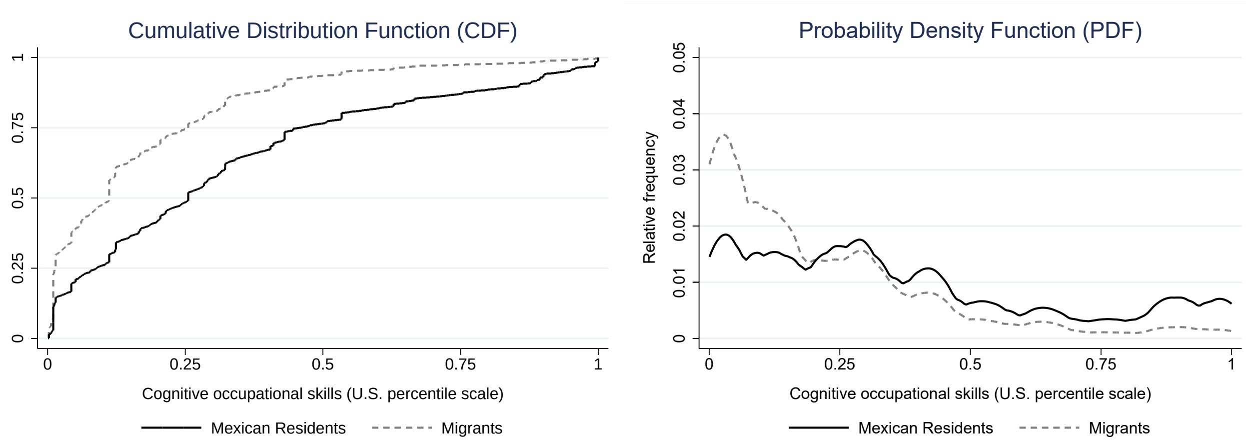
(b) Manual Occupational Skills



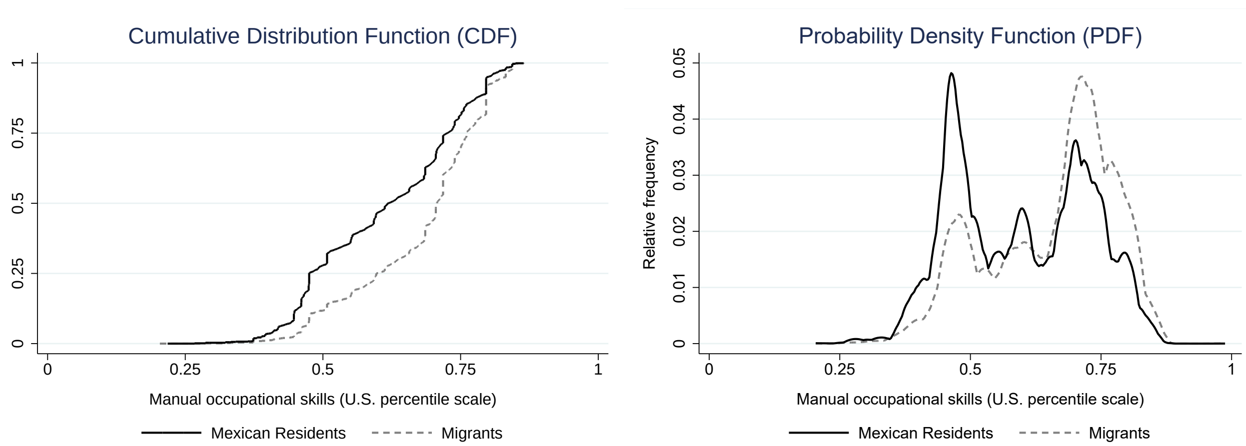
Notes: Figure plots the difference in the CDFs of cognitive and manual skills between migrants and Mexican residents together with 95% confidence intervals for the CDFs in Figure 3. Figures indicate that the CDF of migrants (Mexican residents) first-order stochastically dominates the CDF of Mexican residents (migrants) for manual (cognitive) skills at each point of the distribution. Construction of the differences and the confidence intervals follow Borjas et al. (2019). We use the Stata module DASP (Araar and Duclos, 2013) for the calculations. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Figure A3: Emigrant Selection on Occupational Skills: Results from ENET

(a) Cognitive Occupational Skills



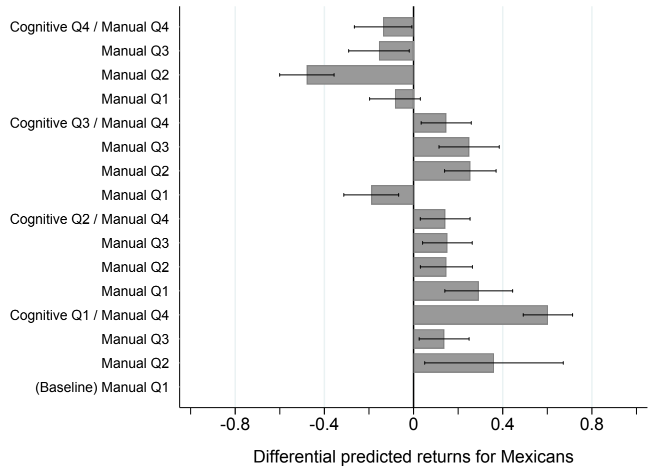
(b) Manual Occupational Skills



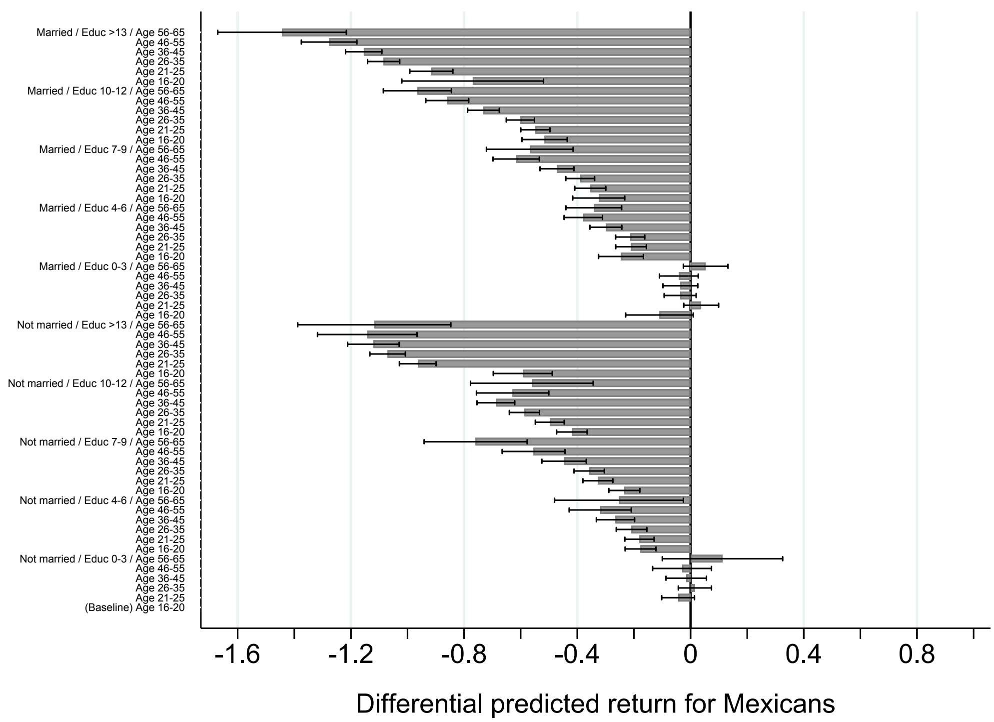
Notes: Figures show cumulative distribution functions (left panels) and probability density functions (right panels) of cognitive occupational skills (Figure A3(a)) and manual occupational skills (Figure A3(b)) by migration status. Sample consists of male Mexicans aged 16–65. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Kolmogorov-Smirnov tests on stochastic dominance indicate that differences between cumulative distribution functions are significant at the 1% level. $N = 10,200$ Mexican migrants in the United States and $N = 2,059,726$ Mexican residents. *Data sources:* ENET, Mexican CONOCER, and U.S. O*NET.

Figure A4: Differential Returns to Skills

(a) Returns to Occupational Skills



(b) Returns to Basic Skills



Notes: Figure plots differential returns to occupational skills (Figure A4(a)) and to basic skills (Figure A4(b)) for recent Mexican migrants in the United States vs. Mexican residents. 95% confidence intervals are based on 1,000 bootstrap replications. Differential returns are expressed relative to the baseline category indicated in the bottom of each figure. *Data sources:* 2000 Mexican Census (10.6% sample), 2000 U.S. Census (5% sample), Mexican CONOCER, and U.S. O*NET.

Table A1: Descriptive Statistics on Migrant Selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ENOE		ENET		MMP		MXFLS	
Period covered in data:	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	1.766		1.807		1.239		1.515	
2nd tertile	0.798	-0.968***	0.832	-0.975***	1.156	-0.083***	0.963	-0.553***
1th (top) tertile	0.447	-1.319***	0.377	-1.430***	0.608	-0.631***	0.543	-0.973***
Manual occupational skills								
3rd (bottom) tertile	0.517		0.461		0.688		0.521	
2nd tertile	0.919	0.402***	0.970	0.508***	1.150	0.463***	0.942	0.422***
1th (top) tertile	1.567	1.050***	1.561	1.100***	1.596	0.908***	1.535	1.014***
For comparison: years of schooling								
0–3 years of schooling	0.977		1.071		0.959		0.735	
4–6 years of schooling	1.355	0.378***	1.389	0.319***	1.100	0.142***	1.209	0.474***
7–9 years of schooling	1.226	0.249***	1.123	0.053*	1.207	0.248***	1.283	0.548***
10–12 years of schooling	0.800	-0.177***	0.670	-0.400***	0.904	-0.055	1.031	0.296
More than 12 years of schooling	0.429	-0.548***	0.255	-0.816***	0.482	-0.477***	0.245	-0.490***
Total observations	2,959,528		2,069,926		471,123		16,164	
U.S. migrants	8,701		10,200		10,464		404	
Average migration rate (in %)	1.35		2.72		2.40		2.50	

Notes: Samples consist of Mexican males aged 16–65. To account for different migrant shares across datasets, we scale the migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) by the share of migrants in the respective dataset to obtain *Migration Propensity*. *Average migration rate* equals the average yearly migration rate, weighting individuals by population weights. Cognitive and manual occupational skills incorporate full observed pre-migration worker history. Difference from the reference category is tested with two-sided t-test. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Emigrant Selection on Occupational Skills: Baseline Results without Skill Interaction

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: migration propensity to the U.S.						
Cognitive skills	–0.126***	–0.127***	–0.125***	–0.104***	–0.100***	–0.084***
	(0.006)	(0.008)	(0.008)	(0.008)	(0.015)	(0.019)
Manual skills	0.205***	0.210***	0.190***	0.130***	0.066**	0.097**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.028)	(0.038)
Years of schooling		0.009*	0.016***	0.036***	0.018***	0.031***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
Age		–0.031***	–0.030***	–0.029***	–0.032***	–0.034***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Fixed Effects						
Birth-by-residence state [1,239]			x			
Municipality [1,499]				x		
Occupation [156]					x	
Narrow labor markets [226,197]						x

Notes: Table reports regressions from Table 2 and Column 4 of Table 8 by omitting the interaction term between cognitive and manual skills. See Table 2 for sample restrictions and further variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,959,528$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table A3: Emigrant Selection on Occupational Skills: Functional Form Robustness Results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: migration propensity to the U.S.						
Cognitive skills	–0.127***	–0.164***	–0.125***		–0.126***	
	(0.008)	(0.009)	(0.008)		(0.008)	
Manual skills	0.210***	0.182***		0.156***		0.159***
	(0.015)	(0.014)		(0.014)		(0.015)
Cognitive skills × manual skills		–0.079***				
		(0.005)				
Years of schooling	0.009*	0.010*	0.006	0.007	0.007	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age	–0.031***	–0.032***	–0.032***	–0.033***	–0.032***	–0.033***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Specification						
Baseline	x	x				
6th-order polynomial			x	x		
Decile fixed effects					x	x

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Skill measures are demeaned and scaled by 10. Column 2 shows baseline results from Column 3 of Table 2; Column 1 shows results from the same model without the cognitive-manual-skill interaction. Columns 3 and 4 contain sixth-order polynomials of manual skills (Column 3) and of cognitive skills (Column 4). Columns 5 and 6 contain decile fixed effects of manual skills (Column 5) and of cognitive skills (Column 6). Decile cutoffs are taken from the occupational skill distribution in the Mexican Census 2000. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,959,528$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table A4: Emigrant Selection on Occupational Skills:
Results by Occupational Skill Category

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: migration propensity to the U.S.						
High manual skills / low cognitive skills	1.181***	1.058***	0.988***	0.786***	0.309***	0.202**
	(0.045)	(0.050)	(0.051)	(0.050)	(0.080)	(0.101)
Low manual skills / low cognitive skills	0.269***	0.209***	0.235***	0.264***	0.167**	0.102
	(0.044)	(0.048)	(0.047)	(0.047)	(0.078)	(0.092)
High manual skills / high cognitive skills	0.139***	0.107**	0.127***	0.164***	0.060	0.057
	(0.041)	(0.042)	(0.043)	(0.043)	(0.074)	(0.097)
Baseline: low manual skills / high cognitive skills						
Years of schooling		–0.017***	–0.010**	0.017***	0.013**	0.028***
		(0.004)	(0.004)	(0.004)	(0.005)	(0.007)
Age		–0.033***	–0.031***	–0.030***	–0.033***	–0.034***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Fixed Effects						
Birth-by-residence state [1,239]			x			
Municipality [1,499]				x		
Occupation [156]					x	
Narrow labor markets [226,197]						x

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Cutoffs for high and low occupational skill categories is the median skill level of the respective skill. Cutoffs for the occupational skill distribution are based on the Mexican population in 2000 and the sample is restricted to Mexican-born males aged 16-65 who are not in school and work between 20 and 84 hours per week. For manual skills, the low-category ranges between 0.203 and 0.577 and the high-category between 0.577 and 0.987 of the U.S. manual skill distribution. For cognitive skills, the low-category ranges between 0.000 and 0.314 and the high-category ranges between 0.314 and 1.000 of the U.S. cognitive skill distribution. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,959,528$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table A5: Emigrant Selection on Occupational Skills: Rural-Urban Divide

	(1)	(2)	(3)	(4)
Dependent variable: migration propensity to the U.S.				
			Urban	Rural
Cognitive skills	–0.164***	–0.139***	–0.154***	–0.124***
	(0.009)	(0.009)	(0.013)	(0.013)
Manual skills	0.182***	0.141***	0.158***	0.102***
	(0.014)	(0.014)	(0.023)	(0.023)
Cognitive skills × manual skills	–0.079***	–0.059***	–0.069***	–0.026***
	(0.005)	(0.005)	(0.008)	(0.007)
Years of schooling	0.010*	0.018***	0.003	0.018**
	(0.005)	(0.005)	(0.007)	(0.008)
Age	–0.032***	–0.031***	–0.028***	–0.032***
	(0.001)	(0.001)	(0.002)	(0.002)
Rural area		0.671***		
		(0.064)		
Observations	2,959,528	2,959,528	2,444,755	514,773
Average migration rate (in %)	1.35	1.35	0.96	2.70

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by sample-specific quarterly migrant share. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. Individuals are considered to live in a rural area when their locality has less than 2,500 inhabitants. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table A6: Selection on Earnings and Differential Returns Using 2010 U.S. ACS Data

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.335***	–0.218***	–0.109***	–0.076**	–0.090***
	(0.026)	(0.030)	(0.029)	(0.031)	(0.031)
Δ basic returns$^{US,2010}_{MEX,2000}$		0.591***		0.222***	0.217***
		(0.061)		(0.063)	(0.064)
Δ occupational returns$^{US,2010}_{MEX,2000}$			1.733***	1.650***	1.658***
			(0.112)	(0.117)	(0.117)
Travel distance to US border					–0.009***
					(0.003)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	–0.044	–0.013	0.050	0.056	0.037
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
3rd quintile	–0.284***	–0.232***	–0.121*	–0.111	–0.136*
	(0.068)	(0.068)	(0.069)	(0.069)	(0.069)
4th quintile	–0.491***	–0.393***	–0.227***	–0.206***	–0.232***
	(0.064)	(0.065)	(0.065)	(0.066)	(0.067)
5th quintile	–0.715***	–0.481***	–0.284***	–0.226***	–0.250***
	(0.059)	(0.066)	(0.064)	(0.068)	(0.069)
Δ basic returns$^{US,2010}_{MEX,2000}$		0.559***		0.181***	0.181***
		(0.061)		(0.064)	(0.064)
Δ occupational returns$^{US,2010}_{MEX,2000}$			1.678***	1.608***	1.619***
			(0.111)	(0.116)	(0.116)
Travel distance to US border					–0.010***
					(0.003)

Notes: Table shows specifications analogous to those in Table 7 with returns to skills in the United States based on the U.S. ACS 2010. See Table 7 for sample restrictions and further variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,950,951$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2010 U.S. ACS (1% sample).

Table A7: Selection on Earnings and Differential Returns Using 2010 U.S. ACS Data: Results from ENET

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.268***	–0.164***	–0.043*	–0.009	–0.042
	(0.020)	(0.025)	(0.026)	(0.028)	(0.029)
Δ basic returns$^{US,2010}_{MEX,2000}$		0.609***		0.271***	0.251***
		(0.056)		(0.056)	(0.056)
Δ occupational returns$^{US,2010}_{MEX,2000}$			1.713***	1.623***	1.630***
			(0.110)	(0.113)	(0.113)
Travel distance to US border					–0.020***
					(0.002)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	0.037	0.077	0.212***	0.217***	0.171***
	(0.061)	(0.062)	(0.064)	(0.064)	(0.065)
3rd quintile	–0.216***	–0.153**	0.037	0.046	–0.023
	(0.058)	(0.060)	(0.061)	(0.062)	(0.063)
4th quintile	–0.474***	–0.367***	–0.125**	–0.107*	–0.183***
	(0.054)	(0.057)	(0.059)	(0.061)	(0.062)
5th quintile	–0.766***	–0.524***	–0.260***	–0.212***	–0.289***
	(0.049)	(0.060)	(0.058)	(0.064)	(0.065)
Δ basic returns$^{US,2010}_{MEX,2000}$		0.512***		0.134**	0.124**
		(0.054)		(0.056)	(0.057)
Δ occupational returns$^{US,2010}_{MEX,2000}$			1.612***	1.565***	1.577***
			(0.103)	(0.108)	(0.108)
Travel distance to US border					–0.022***
					(0.003)

Notes: Table shows specifications analogous to those in Table 7 using ENET and with returns to skills in the United States based on the U.S. ACS 2010. See Table 7 for sample restrictions and further variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,564,772$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENET, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2010 U.S. ACS (1% sample).

Table A8: Selection on Earnings and Differential Returns Using 2010 U.S. ACS Data and 2010 Mexican Census Data

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.318***	–0.204***	–0.078	–0.052	–0.076
	(0.049)	(0.055)	(0.053)	(0.057)	(0.057)
Δ basic returns$^{US,2010}_{MEX,2010}$		0.584***		0.181	0.171
		(0.107)		(0.113)	(0.113)
Δ occupational returns$^{US,2010}_{MEX,2010}$			1.816***	1.747***	1.767***
			(0.194)	(0.204)	(0.204)
Travel distance to US border					–0.018***
					(0.005)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	–0.094	–0.064	0.005	0.010	–0.025
	(0.117)	(0.117)	(0.118)	(0.118)	(0.118)
3rd quintile	–0.290**	–0.239**	–0.118	–0.111	–0.154
	(0.118)	(0.118)	(0.120)	(0.120)	(0.121)
4th quintile	–0.488***	–0.389***	–0.208*	–0.191	–0.234*
	(0.113)	(0.116)	(0.117)	(0.118)	(0.119)
5th quintile	–0.675***	–0.444***	–0.219*	–0.172	–0.210*
	(0.106)	(0.117)	(0.115)	(0.121)	(0.122)
Δ basic returns$^{US,2010}_{MEX,2010}$		0.560***		0.149	0.150
		(0.110)		(0.116)	(0.116)
Δ occupational returns$^{US,2010}_{MEX,2010}$			1.766***	1.708***	1.734***
			(0.193)	(0.203)	(0.203)
Travel distance to US border					–0.019***
					(0.005)

Notes: Table shows specifications analogous to those in Table 7 with returns to skills in the United States based on the U.S. ACS 2010 and in Mexico based in the Mexican Census 2010. The sample is restricted to observations in the years 2010 to 2014. See Table 7 for sample restrictions and further variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 876,077$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2010 Mexican Census (10% sample), and 2010 U.S. ACS (1% sample).

Table A9: Selection on Earnings and Differential Wage Levels

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.335***	–0.340***	–0.303***	–0.307***	–0.318***
	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Δ basic wage levels$^{US,2000}_{MEX,2000}$		–0.120***		–0.135***	–0.133***
		(0.031)		(0.031)	(0.031)
Δ occupational wage levels$^{US,2000}_{MEX,2000}$			–0.095***	–0.101***	–0.101***
			(0.011)	(0.011)	(0.011)
Travel distance to US border					–0.008***
					(0.003)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	–0.044	–0.049	–0.039	–0.045	–0.058
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
3rd quintile	–0.284***	–0.283***	–0.274***	–0.273***	–0.290***
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
4th quintile	–0.491***	–0.486***	–0.469***	–0.462***	–0.481***
	(0.064)	(0.063)	(0.064)	(0.063)	(0.064)
5th quintile	–0.715***	–0.720***	–0.648***	–0.650***	–0.668***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.060)
Δ basic wage levels$^{US,2000}_{MEX,2000}$		–0.103***		–0.118***	–0.116***
		(0.031)		(0.031)	(0.031)
Δ occupational wage levels$^{US,2000}_{MEX,2000}$			–0.092***	–0.097***	–0.097***
			(0.011)	(0.011)	(0.011)
Travel distance to US border					–0.007**
					(0.003)

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. The construction of hourly earnings in Panel A follows Fernández-Huertas Moraga (2011). Hourly earnings are obtained by dividing monthly earnings by 4.5 $\times$ hours worked per week. Earnings quintiles in Panel B depend on hourly earnings. Earnings observations are dropped for persons who are unemployed, not in the labor force, not working in Mexico, and who work less than 20 or more than 84 hours per week. The top and bottom 0.5% of earnings observations are dropped (Chiquiar and Hanson, 2005). Earnings are denoted in constant 2010 U.S. dollars and adjusted for PPP. Δ *wage levels* indicate differential wage levels for observable skills between the United States and Mexico following Kaestner and Malamud (2014). Returns are constructed by calculating differential labor market wage levels for recent Mexican migrants in the United States (immigrated 10 years prior to the survey with an age of 16 years or more at time of arrival) and Mexican residents in the Mexican Census 2000. *Basic wage levels* are predicted from a Mincer-type regression with a full set of interactions between age (six categories), education (five categories), and marital status (two categories). *Occupational wage levels* are predicted from a Mincer-type regression with a full set of interactions between cognitive skills (four categories) and manual skills (four categories). Cutoffs for the occupational skill distribution are based on the Mexican population in 2000. *Travel distance to US border* is the travel distance in hours to the closest border checkpoint. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,950,951$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

B Related Literature

There is an abundant literature dealing with the selection of international migrants (see, e.g., Parey et al. (2017) for an (incomplete) overview). Three observations stand out. First, ever since Borjas (1987), this field of research has expanded rapidly. Second, the large majority of studies use either educational attainment or some measure of earnings as proxies for an individual's productivity or skills. Notable exceptions are Abramitzky et al. (2012), who use occupational information to impute individual earnings by the average earnings in the occupation, and Ramos (1992), who constructs predicted earnings from occupational information. Both papers acknowledge that occupations contain information that is important in determining individual labor-market productivity. Third, previous work has not consistently shown that the observed selection pattern is compatible with the basic Roy/Borjas model predicting that workers migrate when returns to their skills are lower in their home country than abroad.

The literature that specifically deals with the selection of Mexican migration who move to the United States yields similar insights (see Table B1). 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 based on education, age, gender, and marriage status in Mexico from the Mexican Census. 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.[1] However, intermediate selection is not consistent with the predictions of the basic Roy/Borjas model; because returns to education are higher in Mexico than in the United States (e.g., Fernández-Huertas Moraga, 2013), the Roy/Borjas model predicts that Mexican migrants should be negatively selected on education. In line with this prediction, Ibarraran and Lubotsky (2007) observe negative selection when comparing Mexican migrants in the U.S. Census and return migrants in the Mexican Census to non-migrants in the Mexican Census. They explain their contrasting findings compared to Chiquiar and Hanson (2005) by the fact that low-skilled and undocumented migrants are underreported in the U.S. Census (see also Hanson, 2006).

Due to these problems in U.S. Census data, more recent papers use longitudinal Mexican data with rich pre-migration characteristics to study the selection of Mexican emigrants. For instance, drawing on data from the Quarterly National Labor Survey (ENET), Fernández-Huertas Moraga (2011) finds that migrants are negatively selected on actual earnings, while the selection on education is intermediate to negative. This finding of negative earnings selection is confirmed by Villarreal (2016) based on data from ENET's successor, the National Survey of Occupation and

[1] Using the same approach of comparing Mexican migrants in the U.S. Census to Mexican residents in the Mexican Census, Mishra (2007) and Feliciano (2008) argue that Mexican migrants are better educated on average than their peers staying in Mexico.

Employment (ENOE). Using data from the Mexican Family Life Survey (MxFLS), which tracks Mexicans in the United States, Ambrosini and Peri (2012) and Kaestner and Malamud (2014) also document that migrants are negatively selected on actual earnings. Rendall and Parker (2014) combine different datasets to investigate selection over time and consistently find that the average Mexican migrant is negatively selected on education.

Other findings using longitudinal Mexican migrant data are more difficult to rationalize in a Roy/Borjas model. For instance, Orrenius and Zavodny (2005) find intermediate selection on education in the Mexican Migration Project (MMP) data. Moreover, the above work by Fernández-Huertas Moraga (2013) shows *positive* selection on earnings and education in rural Mexico; in Villarreal (2016), Mexican migrants are positively selected on education within occupations.

In sum, the literature on the selection of migrants could not conclusively establish whether the basic Roy/Borjas model can predict migration patterns. The main reasons for these mixed results are the use of different measures to proxy the productive capacity of migrants (education vs. actual or predicted earnings), different sampling frames of the migration data, and different units of analysis (e.g., urban vs. rural areas). While the selection pattern using migrant earnings is mostly consistent with the Roy/Borjas model, such broad skill proxy is uninformative regarding the mechanism behind migrant selection.

Table B1: 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)
Villarreal (2014)	education	–	2005-2012	ENOE (2005-2012)
Villarreal (2016)	education	– / + (within occupations)	2005-2012	ENOE (2005-2012)

Notes: Table shows related papers dealing with 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 sources:* ENADID (Encuesta Nacional de la Dinámica Demográfica): National Survey of Demographic Dynamics, ENE (Encuesta Nacional de Empleo): National Employment Survey, ENET, ENOE, MMP, MxFLS, and Mexican/U.S. Census for various years.

C Details on Skill Measures

A *Construction of Skill Measures Comparable Between Mexico and the United States*

In this section, we provide a detailed description of how we construct the measures of cognitive and manual skills. As laid out in the main text, our final goal is to extract *fundamental* skills that are *comparable* between Mexico and the United States. The derivation of the skill measures proceeds in six steps.

First step: mapping between CONOCER and O*NET domains. The purpose of occupational information surveys such as CONOCER and O*NET is to describe a wide range of information on worker and job characteristics. In each survey, the information is organized into several domains, covering key attributes and characteristics of workers and occupations (see, e.g., O*NET content model; https://www.onetcenter.org/content.html). While both the CONOCER and O*NET capture similar job content information, they inevitably differ to some degree in survey organization, detail, and emphasis on specific domains. This heterogeneity complicates the mapping between the two surveys. To ensure that we match the right survey items in both surveys, we start by mapping domains in CONOCER to domains in O*NET.[2] In Table C1, we match every domain in CONOCER to the appropriate domain in O*NET based on content similarity.[3] In general, we can map every domain in CONOCER to a similar domain in O*NET with a high degree of item similarity (Table C2 shows a list of survey items in each domain used.). The exception is the area of *responsibility* in CONOCER (Panel B of Table C1), which we do not use in the construction of the skill measures because this domain has no counterpart in O*NET. Furthermore, for the domains *cognitive & social skills* (Panel A of Table C1), *skills*, and *abilities* (both Panel B of Table C1), there is more than one domain in O*NET with seemingly similar items. To avoid any inconsistency that may arise from merging items from conceptually different O*NET domains, we map each CONOCER domain to the O*NET domain with most matching items.

One limitation of the CONOCER survey is that questions in the domain *skills* were given only to low-skilled workers, while questions in the domains *abilities* and *knowledge* were given only to high-skilled workers. While the official documentation of the CONOCER survey does not mention why some domains were not given to all workers, a closer inspection of the sample items in these domains suggests that this was due to the fact that these questions were not relevant for the respective group of workers. For example, "skills" consists of items such as on mechanics, construction, installation and maintenance (not relevant for high-skilled workers) while "knowledge" primarily consists of items like human resource, marketing, architecture, chemistry etc. (not relevant for low-

[2] Section C.B shows that ignoring the domains and combining the items within a single step leads to less consistent results.

[3] Our analysis uses O*NET database version 19, released in July 2014, which describes 699 jobs classified in a generally consistent way with the Standard Occupational Classification (SOC).

Table C1: Mapping between CONOCER Domains and O*NET Domains

(1)	(2)	(3)	(4)	(5)	(6)	(7)
CONOCER		O*NET				Remarks
Domain	Items	Domain	Matched items	Related domain	Matched items	
Panel A: Domains used						
Use of tools	10	Work activities	7	—		
Physical abilities	8	Abilities	5	—		
Cognitive & social skills	15	Work styles	12	Skills	7	
Traits	8	Work styles	7	—		
Panel B: Domains not used						
Responsibility	12	—		—		(a)
Skills	10	Tasks	9	Knowledge	9	(b)
Abilities	15	Skills	10	Abilities	3	(c)
Knowledge	25	Knowledge	21	—		(c)

Notes: Column 1 contains the domain labels, which correspond to the questionnaire section in CONOCER. Column 2 gives the total number of items asked in each domain in CONOCER. Column 3 shows the corresponding domain in O*NET and Column 4 contains the number of matched CONOCER items to items in O*NET. Column 5 gives a related domain in O*NET with fewer matching items (given in Column 6). *Remarks:* (a) no corresponding domain in O*NET. (b) questions in CONOCER only given to low-skilled persons. (c) questions in CONOCER only given to high-skilled persons. *Data sources:* Mexican CONOCER and U.S. O*NET.

skilled workers). We leave out domains given to only a subset of CONOCER respondents in the construction of the skill measures.[4] Thus, our skills measures are based on the following CONOCER domains (see Panel A of Table C1): *use of tools, physical abilities, cognitive & social skills*, and *traits*. The corresponding domains in O*NET are *work activities*, *work styles*, and *abilities*.

Second step: separating use-of-office-equipment from use-of-tools. In the second step, we separate items that refer to the use of office equipment (e.g., use of software and use of laboratory equipment) from other items, mainly representing the use of tools in agriculture, industrial production, and construction. Arguably, the nature of these items is very different and the corresponding technology is used by different types of workers (e.g., managerial workers vs. agricultural workers). Therefore, it is very likely that they represent independent sources of variation and thus separate domains.

Third step: mapping between CONOCER and O*NET items within domains. Table C2 shows the list of available survey items within each of the domains we are using. The table also indicates which CONOCER item is mapped to which O*NET item. We accomplish this mapping by inspecting question wording and examples used for collecting the original survey data, since match-

[4] Reassuringly, in the sample of high-skilled workers in CONOCER, our baseline measure of Mexicans' cognitive skills, which does not include questions from the domains *abilities* and *knowledge*, is highly correlated with a cognitive skill measure which also include questions from these two domains ($\rho = 0.89$). Thus, the information loss due to the omission of those CONOCER domains not given to all respondents when constructing our baseline skill measures is likely small.

ing based on item labels alone would be error-prone. We use only the subset of questions in every domain that is comparable between CONOCER and O*NET.[5] Table C2 shows that in some cases, several CONOCER items map to a single O*NET item because CONOCER deals with some areas in more depth than O*NET does (e.g., the O*NET item *operating vehicles, mechanized devices, or equipment* map to the CONOCER items *agricultural machinery*, *industrial machinery*, and *transportation equipment or machinery (vehicles)*). To have a balanced number of items in CONOCER and O*NET, we always use the first available match (in alphabetical order) and ignore the rest of the items.[6] However, we keep all mappable items for comparing the principal components across the surveys (see next step).

Fourth step: use principle component analysis (PCA) within each domain and compare loadings. Subsequently, we use PCA on the survey items within each domain to reduce the data dimensionality and extract only the part of the variation that is common to all items within each domain. While we are not arguing that the remaining variance is purely idiosyncratic, it is likely that this part of the variation is due to particular features of occupations that are not easily comparable across countries. However, before reducing the data dimensionality, we verify in this step that the loadings of the PCAs on the CONOCER and O*NET data, respectively, are similar. This ensures that the domains in both surveys measure similar skill dimensions. Table C3 reports the loadings on the first principal component for each survey item. In Columns 1 and 2 (Columns 3 and 4), we show loadings obtained from a PCA on the CONOCER (O*NET) data. All loadings have the same sign and are normalized to be positive. Reassuringly, we find that all loadings in one survey are usually numerically close to their counterparts in the other survey.[7] Hence, there seems to be a high degree of external validity of the skill dimensions captured by both surveys, despite being based on different populations. The degree of internal reliability is also high, as all domains have a Cronbach's α in the range between 0.79 and 0.96.[8] This suggests that the items within each domain are closely related as a group.

Fifth step: construct intermediate skill scores within domains. In the fifth step, we calculate intermediate skill scores for each domain by using the loadings on the first principal component from the previous step. Before doing so, we aggregate the domains *cognitive & social skills* and *traits* to a single domain because (i) both map to the same domain *work styles* in O*NET and (ii)

[5] Our baseline cognitive and manual skill measures, which are limited to the matched items, are highly correlated with similarly constructed skill measures that are based on the full set of questions in CONOCER ($\rho > 0.85$).

[6] An alternative approach is to average the CONOCER items that map to a single O*NET item rather than dropping all but the first item. This leads to very similar skill measures as our baseline measures ($\rho = 0.99$ for cognitive skills and $\rho = 0.97$ for manual skills).

[7] We can also compute the cosine similarity, which ranges from -1 (i.e., vectors are exactly opposite) to 1 (i.e., vectors are exactly the same), between the vector of loadings for each domain as a similarity measure. The cosine similarity is equal to 0.85 for *use of tools*, 0.99 for *use of office equipment*, 0.98 for *physical abilities,* 0.97 for *cognitive & social skills*, and 0.98 for *traits.* This again indicates a high degree of similarity between the loadings.

[8] The only exception is CONOCER's *use of tools*, whose Cronbach's α is at 0.69, which is still reasonably high.

Table C2: Mapping between CONOCER Items and O*NET Items Within Domains

(1)	(2)	(3)	(4)
CONOCER			O*NET
Variable	Mapped	Used	Matching variable
Use of tools			
Electric tools	Yes	Yes	Repairing and maintaining electronic equipment
Automated industrial machinery (robots)	Yes	Yes	Controlling machines and processes
Agricultural machinery	Yes	Yes	Operating vehicles, mechanized devices, or equipment
Industrial machinery	Yes	No	(Operating vehicles, mechanized devices, or equipment)
Transportation equipment or machinery (vehicles)	Yes	No	(Operating vehicles, mechanized devices, or equipment)
Hand tools	No	No	—
Use of office equipment			
Office equipment	Yes	Yes	Interacting with computers
Software	Yes	No	(Interacting with computers)
School equipment	No	No	—
Laboratory equipment	No	No	—
Physical abilities			
Strength	Yes	Yes	Trunk strength
Coordination and flexibility	Yes	Yes	Extent flexibility
Balance	Yes	Yes	Gross body coordination
Visual	Yes	Yes	Far vision
Hearing	Yes	Yes	Hearing sensitivity
Motoric	No	No	—
Olfactory	No	No	—
Taste	No	No	—
Cognitive & social skills			
Empathy	Yes	Yes	Concern for others
Assertiveness	Yes	Yes	Leadership
Teamwork	Yes	Yes	Cooperation
Attention	Yes	Yes	Attention to detail
Active learning	Yes	Yes	Adaptability/Flexibility
Flexibility	Yes	No	(Adaptability/Flexibility)
Creativity	Yes	Yes	Innovation
Self-control	Yes	Yes	Self-control
Independence	Yes	Yes	Independence
Self-motivatedness	Yes	Yes	Achievement/Effort
Proactivity	Yes	Yes	Initiative
Problem-solving	Yes	Yes	Analytical thinking
Self-knowledge	No	No	—
Verbal communication	No	No	—
Nonverbal communication	No	No	—
Traits			
Cooperation	Yes	Yes	Cooperation
Initiative	Yes	Yes	Initiative
Thoroughness	Yes	Yes	Attention to detail
Responsibility	Yes	Yes	Dependability
Toleration	Yes	Yes	Stress tolerance
Kindness	Yes	Yes	Concern for others
Perseverance	Yes	Yes	Achievement/Effort
Order	No	No	—

Notes: Table contains available survey items in CONOCER and their matches in O*NET. Column 1 contains the items from CONOCER. Column 2 indicates whether there is a corresponding item in O*NET. Column 3 indicates whether the item is actually used for constructing occupational skill measures. Column 4 gives the name of a matching O*NET item. *Data sources:* Mexican CONOCER and U.S. O*NET.

their items map to largely overlapping sets of items. For example, the item "teamwork" in the domain *cognitive & social skills* and the item "cooperation" in the domain *traits* both map to the item "cooperation" in O*NET. Thus, even though *cognitive & social skills* and *traits* are different domains in CONOCER, it is unlikely that they capture independent variation since they map to the same set of O*NET items. We aggregate both CONOCER domains by calculating a weighted average of the values of the components, with the weights determined by the PCA. (We use the same weights for aggregating CONOCER and O*NET scores.) The aggregated skill score captures 94% of the variance of *cognitive & social skills* and *traits* . We keep the label of *cognitive & social skills* to refer to this aggregate skill score.

After the aggregation, we arrive at four intermediate skill scores: use-of-tools skills, physical skills, cognitive & social skills, and use-of-office-equipment skills. Table C4 shows the correlation table for all skill scores when using O*NET-based scores (Panel A) and when using CONOCER-based scores (Panel B). Two observations stand out: First, the correlation structure in Panels A and B is similar, confirming the conclusion from the previous step that the domains in both surveys measure similar skill dimensions. Second, the table shows that scores for physical skills and use-of-tools skills are positively correlated, just as the scores for cognitive & social skills and use-of-office-equipment skills are. This suggests that each pair (physical skills/use-of-tools skills and cognitive & social skills/use-of-office-equipment skills) represents similar baseline skills, and thus there is potential for further aggregation and simplification.

Sixth step: construct final (baseline) skill measures. In the last step, we exploit the correlation of the four intermediate skill measures and combine them to construct our two baseline measures of cognitive and manual skills. Using only the common variation across the intermediate skill scores further ensures that we extract fundamental skills possessed by workers in a certain occupation. As a result of their derivation, these fundamental occupational skills do not depend on particular characteristics of occupations and are therefore directly comparable across borders. We combine the skill measures by using the first principal component of a PCA on the four intermediate skill scores. The manual skill score captures 63% (using CONOCER loadings) and 85% (using O*NET loadings), respectively, of the total variance of the intermediate skill scores; the cognitive skill score captures 78% (using CONOCER loadings) and 88% (using O*NET loadings), respectively (see Table C5). Table C4 shows that our measure of manual skills is strongly positively correlated with the intermediate measures of physical skills and use of tools and the measure of cognitive skills is strongly positively correlated with the intermediate measures of cognitive & social skills and use of office equipment.

For our baseline cognitive and manual skill measures in Mexico, we use the loadings from the O*NET items decomposition (Column 4 of Table C3 and Column 4 of Table C5) and apply them to the responses in the CONOCER survey in accordance with the matching of the items. For constructing U.S. skill scores, we apply the O*NET loading to the responses in the O*NET survey. Thus, we use exactly the same loadings for constructing Mexican and U.S. skill measures. Using the same loadings ensures that the only difference in the skill scores comes from the differences in responses. Given that responses are measured using the same answer scale, we do not need to take any further steps to make the scores directly comparable between Mexico and the United States. The economic reason for denominating Mexican skill measures in the U.S. skill metric is that our economic explanation of the migration behavior is primarily based on the presumption that Mexicans assess the value of their skills in the U.S. labor market.[9]

However, the resulting skill scores are unit-free measures and therefore difficult to interpret. Thus, we convert the raw scores to a percentile scale based on the distribution of the scores in the 2010 U.S. Census. Doing so, we derive our final measures of cognitive and manual occupational skills as percentile scores in the U.S. skill distribution (e.g., see Figure 1 in the main text for the occupational landscape in Mexico in terms of cognitive and manual skills).

[9] In Section C.D, we show that the results obtained from using either O*NET-based or CONOCER-based skill scores are qualitatively similar.

Table C3: Loadings on the First Principal Component

(1)	(2)	(3)	(4)
CONOCER		O*NET	
Variable	Loading	Variable	Loading
Use of tools			
Electric tools	0.71	Repairing and maintaining electronic equipment	0.38
Automated industrial machinery (robots)	0.35	Controlling machines and processes	0.65
Agricultural machinery	0.20	Operating vehicles, mechanized devices, or equipment	0.66
Industrial machinery	0.44	Operating vehicles, mechanized devices, or equipment	—
Transportation equipment or machinery (vehicles)	0.37	Operating vehicles, mechanized devices, or equipment	—
Use of office equipment			
Office equipment	0.78	Interacting with computers	1.00
Software	0.63	Interacting with computers	—
Physical abilities			
Strength	0.58	Trunk strength	0.55
Coordination and flexibility	0.48	Extent flexibility	0.61
Balance	0.55	Gross body coordination	0.51
Visual	0.22	Far vision	0.12
Hearing	0.29	Hearing sensitivity	0.23
Cognitive & social skills			
Empathy	0.24	Concern for others	0.26
Assertiveness	0.30	Leadership	0.41
Teamwork	0.27	Cooperation	0.20
Attention	0.20	Attention to detail	0.17
Active learning	0.31	Adaptability/Flexibility	0.28
Flexibility	0.29	Adaptability/Flexibility	—
Creativity	0.28	Innovation	0.35
Self-control	0.35	Self-control	0.22
Independence	0.31	Independence	0.25
Self-motivatedness	0.28	Achievement/Effort	0.30
Proactivity	0.32	Initiative	0.32
Problem-solving	0.29	Analytical thinking	0.43
Traits			
Cooperation	0.34	Cooperation	0.35
Initiative	0.36	Initiative	0.38
Thoroughness	0.38	Attention to detail	0.23
Responsibility	0.24	Dependability	0.28
Toleration	0.44	Stress tolerance	0.48
Kindness	0.42	Concern for others	0.49
Perseverance	0.42	Achievement/Effort	0.36

Notes: Table shows loadings on the first principal component obtained from a PCA within each domain. Column 1 contains item names from CONOCER. Column 2 gives the loadings using CONOCER data. Column 3 gives the corresponding item from O*NET. Column 4 gives the loadings using O*NET data. *Data sources:* Mexican CONOCER and U.S. O*NET.

Table C4: Correlation Coefficients for Intermediate and Baseline Skill Scores

	(1)	(2)	(3)	(4)	(5)	(6)
	Intermediate skills				Baseline skills	
	Use-of-tools skills	Physical skills	Cognitive & social skills	Use-of-office-equipment skills	Manual skills	Cognitive skills
Panel A: CONOCER-based loadings						
Intermediate skills						
Use-of-tools	1					
Physical skills	0.344	1				
Cognitive & social skills	-0.315	-0.014	1			
Use-of-office-equipment skills	-0.412	-0.367	0.758	1		
Baseline skills						
Manual skills	0.943	0.636	-0.264	-0.469	1	
Cognitive skills	-0.359	-0.114	0.983	0.864	-0.335	1
*Panel B: O*NET-based loadings*						
Intermediate skills						
Use-of-tools skills	1					
Physical skills	0.184	1				
Cognitive & social skills	-0.552	-0.055	1			
Use-of-office-equipment skills	-0.382	-0.392	0.750	1		
Baseline skills						
Manual skills	0.850	0.673	-0.445	-0.497	1	
Cognitive skills	-0.471	-0.200	0.945	0.913	-0.462	1.00

Notes: Table shows correlations between intermediate skill scores and baseline skills scores. Panel A (Panel B) provides correlations when using loadings from the PCA on CONOCER (O*NET) data and applying them to the Mexican population. Observations are at the four-digit occupational level ($N = 443$) and weighted by the Mexican population in 2010. *Data sources:* 2010 Mexican Census, Mexican CONOCER, and U.S. O*NET.

Table C5: Loadings on the First Principal Component Corresponding to Baseline Skill Scores

(1)	(2)	(3)	(4)
CONOCER		O*NET	
Variable	Loading	Variable	Loading
Panel A: Manual skills			
Use-of-tools skills	0.87	Use-of-tools skills	0.73
Physical skills	0.49	Physical skills	0.68
Variance explained	0.63		0.85
Panel B: Cognitive skills			
Use-of-office-equipment skills	0.50	Use-of-office-equipment skills	0.52
Cognitive & social skills	0.87	Cognitive & social skills	0.86
Variance explained	0.88		0.78

Notes: Table shows loadings on first principal component obtained from a PCA on intermediate skill measures. *Variance explained* gives the share of total variance attributed to the first principal component. *Data sources:* Mexican CONOCER and U.S. O*NET.

B Selection on Occupational Skills based on Intermediate and One-Step Skill Measures

Table C6 shows the selection results replacing cognitive and manual skills with the four intermediate skill scores, which are also converted to a percentile scale based on the distribution of the scores in the 2010 U.S. Census. We observe that cognitive and social skills and use-of-office-equipment skills are negatively associated with migration propensity and that use-of-tools skills and physical skills are positively associated with migration propensity. When jointly including all scores in Column 5, we observe relatively large changes in the coefficients. This is in line with the argument from the previous section that there is plenty of shared variation among the four intermediate skill scores. Using only the first component of the intermediate scores, as we do to derive our baseline skills measures, leads to more stable results, which we document in the main text.

The higher degree of consistency in the results using our baseline measures of cognitive and manual skills compared to other ways of deriving skill measures is also indicated by Table C7. Here, we investigate the consistency of our results when estimating our main regressions on samples with different skill intensities.These samples are derived by dropping the four two-digit occupations with the highest/lowest population-weighted percentile scores in the domain indicated in the column header (the table notes list the occupations which are dropped in each specification).[10] Depending on the domain, we drop 10-24% of the baseline sample when imposing this sample restriction. Panel A shows the results from the same regression as in Column 5 of Table C6 estimated on the different samples. While the general selection pattern is largely preserved, the coefficients change quite considerably across samples. We interpret this coefficient instability across samples with different skill intensities as evidence for the intermediate skill scores failing to identify fundamental skills. This interpretation is corroborated by the results in Panel C, where we use only the first principal component of each domain (i.e., our baseline scores). Here, coefficients on the skill measures change only little across samples.

As an alternative to the two-step PCA to construct skill measures, it is also possible to rely on a single-step PCA to combine all survey items from cognitive & social skills/use-of-office-equipment skills to a measure of cognitive skills and from use-of-tools skills/physical skills to a measure of manual skills. In Panel B, we show the results for these one-step skill scores. Reassuringly, we find a similar selection pattern as with our baseline measures, that is, negative selection on cognitive skills and positive selection on manual skills. However, the coefficients again show some instability across samples, indicating that the PCA has difficulties to aggregate items to "cognitive" and "manual" skills when we neglect their domain information. Put differently, the PCA extracts independent sources of variance more cleanly when it is applied to homogeneous sets of items,

[10] Results are qualitatively similar when we drop the three or five two-digit occupations with the highest/lowest skill intensities in a domain.

that is, items from the same domain. In addition, the number of items per domain varies, which contributes to uncertainty about the relative contribution of each domain in the final scores. Given these results, we prefer using cognitive and manual skills from a two-step PCA as our baseline skill measures.

Table C6: Emigrant Selection on Occupational Skills:
Results from Intermediate Skill Scores

	(1)	(2)	(3)	(4)	(5)
Dependent variable: migration propensity to the U.S.					
Cognitive and social skills	–0.179***				–0.105***
	(0.008)				(0.011)
Use-of-office-equipment skills		–0.145***			–0.041***
		(0.008)			(0.010)
Use-of-tools skills			0.332***		0.199***
			(0.017)		(0.019)
Physical skills				0.060***	0.033*
				(0.015)	(0.018)
Years of schooling	–0.007	–0.017***	–0.037***	–0.068***	0.004
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Age	–0.031***	–0.034***	–0.034***	–0.037***	–0.030***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Skill measures are demeaned and scaled by 10. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,959,528$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table C7: Emigrant Selection on Occupational Skills:
Results from Alternative Constructions of Skill Scores

	(1)	(2)	(3)	(4)	(5)
	Full sample	Domains from which occupations are dropped			
		Cognitive & social	Use-of-office-equipment	Use-of-tools	Physical
Panel A: Results from intermediate skill scores					
Dependent variable: migration propensity to the U.S.					
Cognitive & social skills	–0.105***	–0.114***	–0.097***	–0.140***	–0.115***
	(0.011)	(0.015)	(0.016)	(0.017)	(0.012)
Use-of-office-equipment skills	–0.041***	–0.023*	–0.024*	0.009	–0.046***
	(0.010)	(0.014)	(0.014)	(0.015)	(0.011)
Use-of-tools skills	0.199***	0.061***	0.099***	0.117***	0.171***
	(0.019)	(0.023)	(0.024)	(0.024)	(0.021)
Physical skills	0.033*	0.104***	0.095***	0.150***	0.015
	(0.018)	(0.024)	(0.025)	(0.025)	(0.021)
Observations	2,959,528	2,408,586	2,255,312	2,344,259	2,666,851
Panel B: Results from one-step skill scores					
Dependent variable: migration propensity to the U.S.					
Cognitive skills	–0.229***	–0.175***	–0.166***	–0.174***	–0.233***
	(0.010)	(0.014)	(0.014)	(0.013)	(0.010)
Manual skills	0.071***	0.108***	0.126***	0.161***	0.037*
	(0.016)	(0.021)	(0.021)	(0.021)	(0.019)
Cognitive skills × manual skills	–0.069***	–0.072***	–0.076***	–0.082***	–0.057***
	(0.006)	(0.009)	(0.009)	(0.008)	(0.007)
Observations	2,959,528	2,408,586	2,255,312	2,344,259	2,666,851
Panel C: Results from baseline skill scores					
Dependent variable: migration propensity to the U.S.					
Cognitive skills	–0.164***	–0.156***	–0.152***	–0.158***	–0.158***
	(0.009)	(0.013)	(0.014)	(0.012)	(0.009)
Manual skills	0.182***	0.166***	0.184***	0.216***	0.184***
	(0.014)	(0.021)	(0.022)	(0.022)	(0.016)
Cognitive skills × manual skills	–0.079***	–0.071***	–0.074***	–0.077***	–0.079***
	(0.005)	(0.007)	(0.008)	(0.007)	(0.005)
Observations	2,959,528	2,408,586	2,255,312	2,344,259	2,666,851

Notes: Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Skill measures are demeaned and scaled by 10. All regressions contain years of schooling, age, and quarter-by-year fixed effects. Observations are weighted by sampling weights. Columns 2 to 5 report results by dropping the four two-digit level occupations with the highest and lowest population-weighted percentile score in the domain indicated in the column header. Column 2: high: *officials and high authorities of the public, private and social sectors (SINCO 11)*; *auxiliaries and education technicians, instructors, and trainers (SINCO 27)*; *coordinators and heads of area in financial, administrative, and social services (SINCO 15)*; *doctors, nurses and other health specialists (SINCO 24)*; low: *operators of agricultural and forestry machinery (SINCO 63)*; *workers in agricultural and livestock activities (SINCO 61) and their support workers (SINCO 91)*; *domestic, cleaning, ironers, and other cleaning workers (SINCO 96)*. Column 3: high: *directors and managers of sales, restaurants, and hotels (SINCO 14)*; *coordinators and heads of area in financial, administrative and social services (SINCO 15)*; *directors and managers in financial, administrative and social services (SINCO 12)*; *auxiliaries and technicians in economic-administrative sciences, social sciences, humanists and arts (SINCO 25)*; low: *operators of agricultural and forestry machinery (SINCO 63)*; *workers in agricultural and livestock activities (SINCO 61) and their support workers (SINCO 91)*; *construction workers (SINCO 71)*. Column 4: high: *operators of agricultural and forestry machinery (SINCO 63)*; *workers in agricultural and livestock activities (SINCO 61) and their support workers (SINCO 91)*; *operators of facilities and industrial machinery (SINCO 81)*; low: *coordinators and heads of sales area, restaurants, and hotels (SINCO 17)*; *directors and managers in financial, administrative, and social services (SINCO 12)*; *merchants in establishments (SINCO 41)*; *workers in the rental (SINCO 43)*. Column 5: high: *armed forces (SINCO 54)*; *helpers of transport drivers (SINCO 93)*; *auxiliaries and education technicians, instructors, and trainers (SINCO 27)*; *workers in fishing, forestry, hunting and similar activities (SINCO 62)*; low: *auxiliaries and technicians in economic-administrative sciences, social sciences, humanists, and arts (SINCO 25)*; *street sellers (SINCO 95)*; *workers who provide and manage information (SINCO 32)*; *domestic, cleaning, ironers, and other cleaning workers (SINCO 96)*. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

C Construction of Interpersonal, Intrapersonal, and Communication Skill Measures

In this section, we provide details about the construction of communication skills, interpersonal skills, and intrapersonal skills. We also compare the measures to our baseline measures of cognitive and manual skills. We follow the procedure described in Section C.A, except that we divide the items used to construct cognitive skills into interpersonal and intrapersonal subgroups. The subgroups are given in Panel A and B of Table C8. For guidance how to assign items to the different subgroups, we use the report by the National Research Council (2012).[11] To construct the measures of interpersonal and intrapersonal skills, we first perform a separate PCA in each domain to extract the component with the most shared variance. However, in contrast to deriving our baseline cognitive skill measure, these PCA's are based only on the subset of items from each domain that can meaningfully be assigned to either interpersonal or intrapersonal skills. With a few exceptions, the loadings obtained in CONOCER and O*NET are very similar. Following the final step from the approach described in Section C.A, we combine the resulting intermediate scores using a second PCA to derive our measures of interpersonal skills and intrapersonal skills, respectively. Table C9 shows that both measures are positively (negatively) correlated with our baseline measures of cognitive (manual) skills. For the selection analysis, we express interpersonal and intrapersonal skills in the U.S. skill metric by using the loadings obtained from O*NET data.

We also construct a measure of communication skills, which is based on the item "verbal communication" in CONOCER (see Panel C of Table C8). The measure is similar to the basic communication skills in Peri and Sparber (2009), who use the items "oral expression" and "written expression" to construct their baseline communication skills measure. Because only one item measures communication skills in CONOCER, we do not perform any further calculations. To measure communication skills in O*NET, we use the score corresponding to the first principal component of the items "oral expression" and "written expression." It is important to note that "verbal communication" is not part of our baseline cognitive skill measure because "verbal communication" in CONOCER and "oral expression" and "written expression" in O*NET belong to different skill domains and are therefore not mapped. Table C9 shows that our measure of communication skills is strongly positively correlated with cognitive skills as well as with interpersonal and intrapersonal skills.

[11] Note that the National Research Council (2012) distinguishes three different skills: *cognitive*, *intrapersonal,* and *interpersonal* skills. However, when it comes to the skills of migrants, it is more interesting to focus on the dichotomy between interpersonal/communications skills vs. other non-manual skills. Therefore, we do not make the distinction between cognitive and intrapersonal skills as it is done by the National Research Council. Another reason for not making such distinction is that their cognitive domain is usually tested with standardized assessments (such as IQ tests), which our data do not provide.

Table C8: Loadings on the First Principal Component for Interpersonal, Intrapersonal, and Communication Skills

(1)	(2)	(3)	(4)
CONOCER		O*NET	
Variable	Loading	Variable	Loading
Panel A: Interpersonal skills			
Cognitive & social skills			
Empathy	0.51	Concern for others	0.63
Assertiveness	0.61	Leadership	0.66
Teamwork	0.61	Cooperation	0.40
Traits			
Cooperation	0.48	Cooperation	0.44
Toleration	0.63	Stress tolerance	0.57
Kindness	0.61	Concern for others	0.70
Panel B: Intrapersonal skills			
Cognitive & social skills			
Attention	0.23	Attention to detail	0.21
Active learning	0.37	Adaptability/Flexibility	0.29
Creativity	0.35	Innovation	0.43
Self-control	0.42	Self-control	0.19
Independence	0.37	Independence	0.29
Self-motivatedness	0.33	Achievement/Effort	0.36
Proactivity	0.39	Initiative	0.36
Problem-solving	0.34	Analytical thinking	0.55
Traits			
Initiative	0.49	Initiative	0.60
Thoroughness	0.56	Attention to detail	0.38
Responsibility	0.33	Dependability	0.32
Perseverance	0.58	Achievement/Effort	0.62
Panel C: Communication skills			
Verbal communication	1	Oral expression	0.61
Verbal communication	—	Written expression	0.79

Notes: Table shows loadings on the first principal component obtained from a PCA within each subgroup. Column 1 contains item names from CONOCER. Column 2 gives the loadings using CONOCER data. Column 3 gives the corresponding item from O*NET. Column 4 gives the loadings using O*NET data. *Data sources:* Mexican CONOCER and U.S. O*NET.

Table C9: Correlation between Alternative Cognitive Skill Scores

	(1)	(2)	(3)	(4)	(5)
	Cognitive	Communication	Interpersonal	Intrapersonal	Manual
Cognitive	1				
Communication	0.816	1			
Interpersonal	0.902	0.875	1		
Intrapersonal	0.994	0.819	0.913	1	
Manual	-0.462	-0.505	-0.453	-0.493	1

Notes: Table shows correlations between cognitive, communication, interpersonal, intrapersonal, and manual skill scores. Occupational skills are constructed using loadings from O*NET data. Observations are at the four-digit occupational level ($N = 443$) and weighted by the Mexican population in 2010. *Data sources:* 2010 Mexican Census, Mexican CONOCER, and U.S. O*NET.

D Selection on Occupational Skills based on Mexican CONOCER-based Skill Measures

As detailed in Section C.A, our main analysis uses loadings obtained from the U.S. O*NET to construct comparable skill measures across borders because our economic explanation of the migration behavior is primarily based on the idea that Mexicans evaluate the value of their skills in the U.S. labor market. In principle, however, it is also possible to express skills in the Mexican skill metric using loadings from the Mexican CONOCER. In this section, we compare the results from using CONOCER-based skill scores to our baseline results using O*NET-based skill scores.

The first thing to observe is that Table C10 shows a high correlation between CONOCER-based and O*NET-based scores ($\rho = 0.99$ for cognitive skills and $\rho = 0.87$ for manual skills). Table C11 compares our results using the U.S. skill metric (Column 1, baseline) and the Mexican skill metric (Column 3). Because we express our baseline measures in the U.S. skill distribution, we also provide estimates how the results change when using the Mexican skill distribution to construct percentile skill scores (Column 2). In fact, when expressing O*NET-based skill scores in the Mexican skill distribution (Column 2), the manual skill coefficient is smaller than when expressing them in the U.S. skill distribution (Column 1). Because the level of manual skills is lower in the United States than in Mexico, the same *absolute* difference in manual scores between migrants and non-migrants is relatively higher when expressed in terms of the U.S. manual skill distribution than in terms of the Mexican manual skill distribution (standard deviation of raw manual skill scores is 1.53 in the 2010 U.S. Census and 0.63 in 2010 Mexican Census). For cognitive skills, coefficients in the U.S. skill distribution are very similar as in the Mexican skill distribution because the cognitive skill distributions in both countries are very similar (standard deviation of raw cognitive skill scores is 1.32 in the 2010 U.S. Census and 1.52 in 2010 Mexican Census). Hence, when we standardize skills using the sample-specific standard deviation (i.e., we divide the scores in the U.S. skill distribution by the U.S.-specific standard deviation and the scores in the Mexican skill distribution by the Mexico-specific standard deviation), coefficients in the U.S. skill distribution and Mexican skill distribution are almost identical (Columns 4 and 5 of Table C11). This shows that the magnitude of selection is independent of the skill distribution used once we account for level differences in skill distributions across countries to make them comparable.

Examining the results when expressing the skill measures in the Mexican skill metric using loadings obtained from CONOCER to construct skill scores (Columns 3 and 6 of Table C11), we can again confirm the baseline selection pattern, that is, negative selection on cognitive skills and positive selection on manual skills. However, the coefficient on manual skills suggests a weaker selection and the coefficient on cognitive skills suggests a stronger selection compared to using the O*NET rotations (Column 1 and 4). The main reason is the relatively large fraction of workers in Mexico who are active in the agricultural sector, which relies less on use-of-tools skills than

Table C10: Correlation between O*NET- and CONOCER-based Skill Scores

		(1)	(2)	(3)	(4)
		Cognitive skills		Manual skills	
		O*NET	CONOCER	O*NET	CONOCER
Cognitive skills	O*NET	1			
Cognitive skills	CONOCER	0.988	1		
Manual skills	O*NET	-0.184	-0.162	1	
Manual skills	CONOCER	-0.293	-0.268	0.874	1

Notes: Table shows correlations between skill scores using either loadings obtained from a PCA on O*NET items or a PCA on CONOCER items. Observations are at the four-digit occupational level ($N = 443$). *Data sources:* Mexican CONOCER and U.S. O*NET.

the agricultural sector in the United States. This can be seen in Figures C1 and C2, where we compare O*NET-based and CONOCER-based skill scores for our baseline skills and the four intermediate skills. To facilitate interpretation, the scores are averaged at the two-digit occupational level (using ENOE population weights for the aggregation). While most of the occupations show a slightly higher manual intensity when using CONOCER-based scores, O*NET-based scores are substantially larger than their CONOCER-based counterparts in three occupations: agricultural and livestock activities (occupation 61), operators of agricultural and forestry machinery (occupation 63), and their support workers (occupation 91) (Figure C1). According to Figure C2, this difference is due to the fact that O*NET-based scores assign higher use-of-tools skills to workers in these three occupations. This may represent a higher use of technology in the U.S. agricultural sector than in the Mexican agricultural sector. While it is beyond the scope of the paper to provide an in-depth analysis of the causes and consequences of these differences, it is likely that the low use-of-tool intensity in Mexican agriculture is driven by a large supply of relatively cheap labor (see also Lewis (2011) for a discussion of lower tool utilization in the presence of a large supply of supplementary labor). Since the low use-of-tool intensity in Mexico also means the absence of large capital-skill complementarities, which would be beneficial for earnings, it may also partly explain the high migration rate of Mexican agricultural workers.

To examine to what extent such (technology-driven) difference in the agricultural sectors between Mexico and the United States affects our main results, we exclude occupations 61, 63, and 91 from the sample (Panel B of Table C11). Columns 1 and 4 show that results with our baseline skill measures are highly robust to the exclusion of these agricultural workers. When comparing Columns 2 and 3 and Columns 5 and 6, respectively, we observe that using O*NET loadings and CONOCER loadings to construct skills leads to very similar results in the restricted sample.

Finally, for assessing whether O*NET or CONOCER rotations should be used to construct skill scores, it matters whether Mexican migrants assess their skills in the U.S. skill distribution or in the Mexican skill distribution. We infer this from studying the role of differential occupational returns

Table C11: Emigrant Selection on Occupational Skills:
Results Using Loadings Obtained from CONOCER to Construct Skill Measures

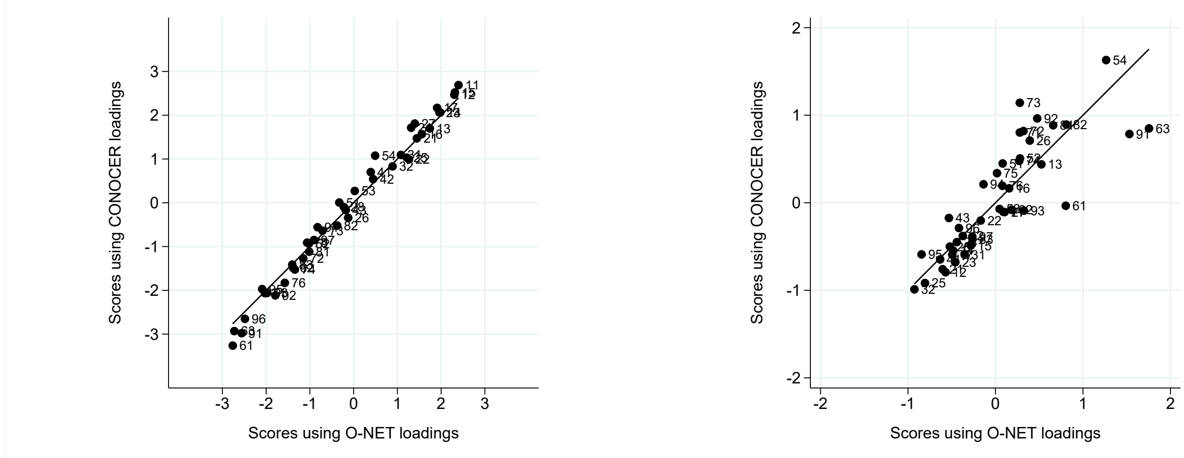
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficients:	Not standardized			Standardized		
Weighting:	U.S.	Mexico		U.S.	Mexico	
Loading:	O-NET	O-NET	CONOCER	O-NET	O-NET	CONOCER
Panel A: Full sample						
Dependent variable: migration propensity to the U.S.						
Cognitive skills	–0.164***	–0.179***	–0.216***	–0.047***	–0.045***	–0.060***
	(0.009)	(0.010)	(0.010)	(0.002)	(0.002)	(0.003)
Manual skills	0.182***	0.096***	0.030***	0.024***	0.027***	0.008***
	(0.014)	(0.007)	(0.008)	(0.002)	(0.002)	(0.002)
Cognitive skills $\times$ manual skills	–0.079***	–0.043***	–0.028***	–0.003***	–0.003***	–0.002***
	(0.005)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)
Observations	2,959,528	2,959,528	2,959,528	2,959,528	2,959,528	2,959,528
Panel B: Excluding agricultural workers						
Dependent variable: migration propensity to the U.S.						
Cognitive skills	–0.154***	–0.167***	–0.148***	–0.045***	–0.042***	–0.041***
	(0.012)	(0.013)	(0.013)	(0.003)	(0.003)	(0.003)
Manual skills	0.184***	0.092***	0.087***	0.024***	0.025***	0.022***
	(0.021)	(0.010)	(0.010)	(0.003)	(0.003)	(0.003)
Cognitive skills $\times$ manual skills	–0.074***	–0.039***	–0.036***	–0.003***	–0.003***	–0.003***
	(0.007)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)
Observations	2,576,465	2,576,465	2,576,465	2,576,465	2,576,465	2,576,465

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. *Standardized coefficients* report results from regressions on the skills measures that are divided by the sample standard deviation. *Weighting* refers to the population with which the scores are weighted. *Loading* refers to the loadings from the PCA taken from either U.S. O*NET or Mexican CONOCER. Skill measures are demeaned and scaled by 10. All regressions control for years of schooling, age, and quarter-by-year fixed effects. *Panel B* excludes workers in agricultural and livestock activities (occupation 61), operators of agricultural and forestry machinery (occupation 63), and their support workers (occupation 91). Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

in explaining migrant selection and selection on earnings (see also Section V in the main text). Table C12 presents the results. Columns 1 to 4 show that O*NET-based returns are better able to explain selection on earnings than CONOCER-based returns (or basic returns) because including them leads to the strongest decrease in the coefficient on earnings. As selection on earnings is indicative about the structure of migration benefits (i.e., the negative selection on earnings implies that those with the highest earnings in Mexico are those with the lowest benefits of migrating), this finding strongly suggests that migrants evaluate the earnings potential of their skills within the U.S. skill distribution (and not within the Mexican skill distribution). This conclusion is confirmed when we include differential returns pairwise in Columns 5 to 7 and when we include all three differential returns in Column 8, since O*NET-based returns always outperform CONOCER-based returns (as well as basic returns). Thus, we consider it most appropriate to use O*NET loadings to calculate skill scores.

Figure C1: Comparison of Raw Skill Scores Using Loadings Obtained from O*NET and CONOCER: Baseline Occupational Skills

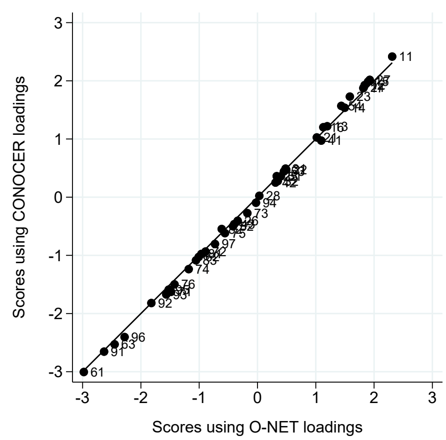
(a) Cognitive Skills **(b)** Manual Skills



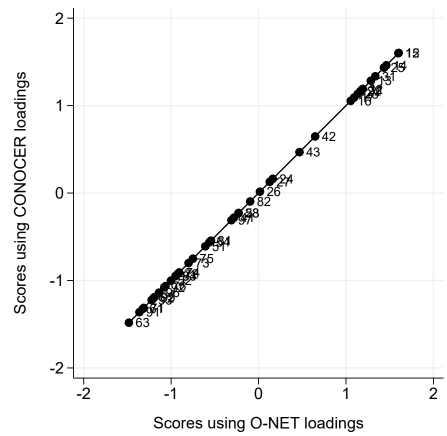
Notes: Figure plots average raw scores for two-digit occupations, which are obtained by either using loadings obtained from O*NET or CONOCER. The solid black line represents a 45° line. Averages are weighted by the population in the analytical ENOE sample. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Figure C2: Comparison of Raw Skill Scores Using Loadings Obtained from O*NET and CONOCER: Intermediate Occupational Skills

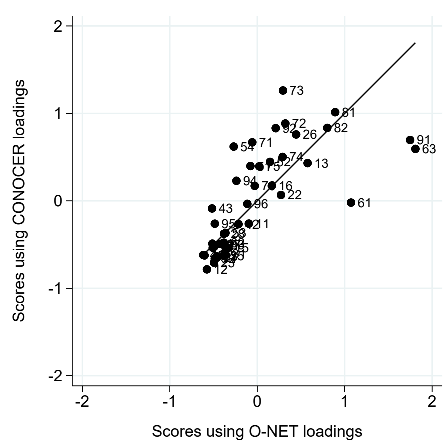
(a) Social and Cognitive Skills



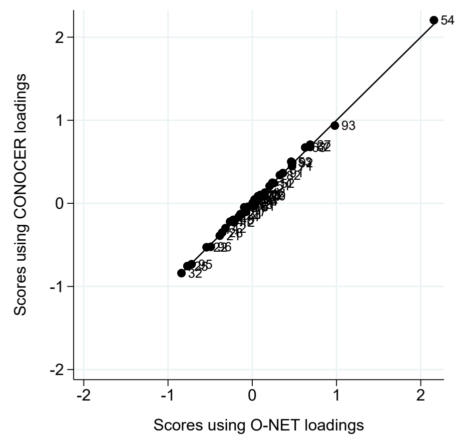
(b) Use-of-office-equipment Skills



(c) Use-of-tools Skills



(d) Physical Skills



Notes: Figure plots average raw scores for two-digit occupations, which are obtained by either using loadings obtained from O*NET or CONOCER. The solid black line represents a 45° line. Averages are weighted by the population in the analytical ENOE sample. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table C12: Selection on Earnings and Differential Returns:
Results Using Loadings Obtained from CONOCER to Construct Skill Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Mean selection on earnings								
Dependent variable: migration propensity to the U.S.								
Log hourly earnings	–0.335***	–0.170***	–0.075***	–0.183***	–0.038	–0.091***	–0.058*	–0.025
	(0.026)	(0.031)	(0.029)	(0.028)	(0.031)	(0.031)	(0.029)	(0.032)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.719***			0.246***	0.506***		0.224***
		(0.056)			(0.061)	(0.057)		(0.061)
Δ occupational returns$^{US,2000}_{MEX,2000}$ (O-NET)			1.611***		1.493***		1.433***	1.341***
			(0.091)		(0.099)		(0.093)	(0.099)
Δ occupational returns$^{US,2000}_{MEX,2000}$ (CONOCER)				1.298***		1.089***	0.396***	0.361***
				(0.112)		(0.115)	(0.115)	(0.116)
Panel B: Selection along the earnings distribution								
Dependent variable: migration propensity to the U.S.								
2nd quintile	–0.044	–0.002	0.046	0.044	0.053	0.058	0.063	0.067
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
3rd quintile	–0.284***	–0.209***	–0.124*	–0.153**	–0.111	–0.124*	–0.103	–0.094
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.069)	(0.068)
4th quintile	–0.491***	–0.350***	–0.218***	–0.309***	–0.192***	–0.243***	–0.194***	–0.173***
	(0.064)	(0.065)	(0.065)	(0.065)	(0.066)	(0.066)	(0.066)	(0.066)
5th quintile	–0.715***	–0.383***	–0.209***	–0.425***	–0.139**	–0.248***	–0.180***	–0.121*
	(0.059)	(0.066)	(0.064)	(0.062)	(0.068)	(0.068)	(0.065)	(0.069)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.688***			0.215***	0.461***		0.189***
		(0.056)			(0.061)	(0.058)		(0.062)
Δ occupational returns$^{US,2000}_{MEX,2000}$ (O-NET)			1.560***		1.457***		1.384***	1.309***
			(0.090)		(0.098)		(0.092)	(0.098)
Δ occupational returns$^{US,2000}_{MEX,2000}$ (CONOCER)				1.265***		1.065***	0.379***	0.345***
				(0.111)		(0.115)	(0.115)	(0.116)

Notes: Occupational returns are predicted from a Mincer-type regression with a full set of interactions between cognitive skills (four categories) and manual skills (four categories). Categories are constructed from skill scores based on rotations from CONOCER to calculate Δ occupational returns$^{US,2000}_{MEX,2000}$ (CONOCER) and based on rotations from O-NET to calculate Δ occupational returns$^{US,2000}_{MEX,2000}$ (O-NET). Cutoffs for the occupational skill distribution are based on the Mexican population in 2000. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,950,951$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p$<$0.01, ** p$<$0.05, * p$<$0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

D Data Details

A Further Datasets to Identify Mexican Emigrants

Mexican Labor Force Survey (ENET)

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). Besides covering an earlier time period, the survey is similar to ENOE.

Mexican Migration Project (MMP)

The MMP is a bi-national 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. Thus, the MMP is representative for immigrant-sending communities, providing a sample of mainly urban communities with relatively high emigration propensities. Areas sampled in the MMP are identified by surveying Mexican migrants in the United States and then surveying their home community in Mexico.[12] The survey started in 1982 and has been conducted annually since 1987. We use the MMP143 database with 143 communities, released in 2013. At each interview, a retrospective life history of the household head is gathered. This includes, among other things, migration experience, work history (including occupational information at the three-digit level), and marriage behavior.

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 *migrants* as males aged 16 to 65 years who lived in Mexico at year t and left for the United States the year after. *Mexican residents* are those who lived in Mexico in years t and $t + 1$.[13] We again focus on males and restrict the analysis to household heads because they most likely make the decision about whether or not to migrate.

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) and to study path dependencies of occupational choices. Since retrospective information on workers' occupational histories in the MMP reach far back in time, we can also investigate how the pattern of selection changed over time, for instance, due to changes in U.S. immigration policies. The MMP further includes information about the legal status of Mexican migrants. Selection on occupational skills may differ between legal and illegal migrants because of differences in the deportation risk and in the degree to which skills can be transferred from Mexico to the United States, both potentially affecting occupational choices and acquired skills.

Mexican Family Life Survey (MxFLS)

The MxFLS is a nationally representative household panel that follows individuals and households over time. The first round, in which about 8,000 households in Mexico were surveyed, took place in 2002. The second and third rounds took place in 2005 and 2009, respectively. A unique feature of the survey is that respondents are followed even to the United States, with re-contact rates for migrants and non-migrants as high as 90%.

The main advantage of the survey is that it is representative of the Mexican population and also covers entire households that emigrated to the United States. Thus, it avoids the potential sample selection problem of missing households in the Mexican data (Steinmayr, 2014). Because

[12]Due to this sampling design, these areas have a migration propensity above the Mexican average.

[13]We drop years before 1950 because there was very little migration in the first half of the 20th century.

the survey does not rely on retrospective information, the problem of recall bias is also reduced. However, the main disadvantages of the survey in the context of our study are the relatively small sample size of the migrant population and that information on occupations is provided only at the two-digit level (in total, only 18 occupations). Due to the coarse occupational information, the MxFLS-based measures of cognitive and manual skills will likely yield considerable measurement error. Despite these limitations of the MxFLS data, we use the survey to show that our results are robust to different sampling frames and whole-household migration.

B Occupation Crosswalks

Before Q2-2012, ENET and ENOE used the four-digit Mexican Classification of Occupations (Clasificación Mexicana de Ocupaciones—CMO) to classify occupations. Afterward, ENOE started to report occupations in the four-digit National Occupation Classification System (Sistema Nacional de Clasificación de Ocupaciones—SINCO) (for details on SINCO, see INEGI, 2011a). SINCO was introduced to make the occupational classification more comparable with other international classification systems and with classification systems of Mexico's main trading partners (i.e., USA and Canada). CONOCER, which we use to construct our skill measures, also reports occupational information using the SINCO classification at the four-digit level.

We use a crosswalk between SINCO and CMO (provided by INEGI, 2011b) to convert CMO occupations into SINCO occupations for periods before Q2-2012. Out of 448 CMO occupational codes, 373 occupations (83%) have a direct and unique equivalent in SINCO. For the remaining 75 CMO occupations, we use the SINCO occupation with the largest weight, calculated as the share of workers for each occupational code within a given CMO occupation (based on ENOE Q3-2012 to Q2-2013). This weight is on average 74%, meaning that there is mostly one large SINCO occupation corresponding to the respective CMO occupation. We also experimented with using skill score averages over the multiple SINCO occupations that relate to one specific CMO occupation (instead of picking the one with the largest weight). This procedure yields very similar skill measures ($r > 0.99$ for cognitive and manual skills).

The MMP provides occupational information at the three-digit level, also reported using the CMO classification. Here, we use skill averages over the CMO occupations based on the four-digit SINCO occupations to construct occupational skill measures. Skill scores are weighted by the share of workers in each SINCO occupation within a given CMO occupation (based on ENOE Q3-2012 to Q2-2013). We apply the same procedure to construct skill measures in the MxFLS data, where occupational information is provided in the CMO classification at the two-digit level.

C Descriptive Statistics

Table D1 provides summary statistics on migration rates, occupational skills, and main control variables for ENOE, ENET, MMP, and MxFLS surveys. Due to the different sampling periods, migration rates vary across datasets, from 1.4% in ENOE (0.34% per quarter) to 2.4% in MMP, 2.5% in MxFLS, and 2.7% in ENET (0.68% per quarter). However, the observed occupational skills are strikingly similar. Consistently across datasets, the average Mexican worker has relatively high manual skills and relatively low cognitive skills compared to his U.S. peer. The percentile ranks are very similar to those in the Mexican Census data (see Figure 1).[14]

We find substantial variation in skills within broader occupational groups (see Table D2). Using ENOE, the skill range (difference between maximum skills and minimum skills) within one-digit occupations is 66 percentiles for cognitive skills and 48 percentiles for manual skills. At the two-digit level (43 occupations), we find a skill range of 43 percentiles for cognitive skills and 34 percentiles for manual skills. Even at the three-digit level (144 occupations), there is substantial variation in skills (21 percentiles for cognitive skills and 17 percentiles for manual skills). These large skill differences within occupational groups make a strong case for using our measures to categorize and rank occupations, because we can take into account both the large skill heterogeneity within broader occupational groups and skill similarities across occupational borders.

Strikingly, the ENOE data show that during the (at most) four pre-migration quarters 50% of individuals change their one-digit occupation at least once, suggesting a large degree of occupational mobility. However, if we look at the associated change in occupational scores, we find that workers tend to switch to occupations requiring similar skills. For manual skills, the median (mean) skill range is only 3 percentiles (9 percentiles) (i.e., 7% (18%) of the full skill range within one-digit occupations). For cognitive skills, the median (mean) skill range is 6 percentiles (16 percentiles) (i.e., 9% (24%) of the full skill range).[15] This analysis of the (skill) mobility of workers provides support for the idea that our occupation-level skill measures are a meaningful summary of individual's actual skills.

[14] See Section V for the construction and interpretation of the returns measures in Table D1.

[15] This result is consistent with evidence from the United States and Germany showing that individuals try to move to skill-related occupations to avoid the loss of specific human capital (Gathmann and Schönberg, 2010; Nedelkoska et al., 2017; Robinson, 2018).

Table D1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
Variable	Mean	SD	Min	Max	N
Panel A: ENOE					
Cognitive skills (percentile)	0.3320	0.2888	0.0006	1.0000	2,959,528
Cognitive skills (score)	-0.8695	1.4877	-3.8503	3.2256	2,959,528
Manual skills (percentile)	0.6100	0.1332	0.2039	0.9875	2,959,528
Manual skills (score)	0.1307	0.6175	-1.8153	2.5320	2,959,528
Migrated to the U.S. (quarterly share)	0.0034	–	0	1	2,959,528
Years of schooling	9.0825	4.4436	0	24	2,959,528
Age	36.8891	12.9577	16	65	2,959,528
Rural status	0.2262	–	0	1	2,959,528
Log real hourly earnings (2010 U.S. dollars)	0.9613	0.7044	-2.0225	3.2797	1,950,951
Travel distance to U.S. border (hours)	10.269	5.3663	0.0539	26.6936	1,950,951
Δ basic returns$^{US,2000}_{MEX,2000}$	-0.4804	0.3405	-1.4432	0.1129	1,950,951
Δ basic returns$^{US,2010}_{MEX,2000}$	-0.1352	0.3119	-1.1766	0.4582	1,950,951
Δ occupational returns$^{US,2000}_{MEX,2000}$	0.1442	0.2684	-0.4785	0.6027	1,950,951
Δ occupational returns$^{US,2010}_{MEX,2000}$	0.1138	0.2335	-0.3226	0.5478	1,950,951
Panel B: ENET					
Cognitive skills (percentile)	0.3212	0.2887	0.0006	1.0000	2,069,926
Cognitive skills (score)	-0.9367	1.4909	-3.8503	2.9664	2,069,926
Manual skills (percentile)	0.6147	0.1328	0.2039	0.9875	2,069,926
Manual skills (score)	0.1528	0.6206	-1.8153	2.5320	2,069,926
Migrated to the U.S. (quarterly share)	0.0068	–	0	1	2,069,926
Years of schooling	7.8243	5.3314	0	22	2,069,926
Age	35.7065	13.0269	16	65	2,069,926
Rural status	0.2278	–	0	1	2,069,926
Log real hourly earnings (2010 U.S. dollars)	0.8474	0.8954	-2.6531	3.3652	1,564,772
Travel distance to U.S. border (hours)	10.3294	5.1784	0.0539	26.6936	1,564,772
Δ basic returns$^{US,2000}_{MEX,2000}$	-0.4198	0.3415	-1.4432	0.1129	1,564,772
Δ basic returns$^{US,2010}_{MEX,2000}$	-0.0843	0.3051	-1.1766	0.4582	1,564,772
Δ occupational returns$^{US,2000}_{MEX,2000}$	0.1568	0.2750	-0.4785	0.6027	1,564,772
Δ occupational returns$^{US,2010}_{MEX,2000}$	0.1247	0.2408	-0.3226	0.5478	1,564,772
Panel C: MMP					
Cognitive skills (percentile)	0.2121	0.2437	0.0155	1.0000	471,123
Cognitive skills (score)	-1.5300	1.3157	-2.7137	2.9664	471,123
Manual skills (percentile)	0.6759	0.1338	0.1964	0.8389	471,123
Manual skills (score)	0.5231	0.6785	-1.7489	1.5942	471,123
Migrated to the U.S. (annual share)	0.024	–	0	1	471,123
Years of schooling	5.5225	4.4830	0	25	471,123
Age	34.4605	12.4148	16	65	471,123
Panel D: MxFLS					
Cognitive skills (percentile)	0.2868	0.2330	0.0384	0.9598	16,164
Cognitive skills (score)	-1.1032	1.2121	-2.5674	2.0561	16,164
Manual skills (percentile)	0.6320	0.1057	0.4005	0.7770	16,164
Manual skills (score)	0.2682	0.5310	-0.8926	1.0356	16,164
Migrated to the U.S. (annual share)	0.025	–	0	1	16,164
Years of schooling	7.6229	4.2449	0	18	16,164
Age	36.4923	13.4591	16	65	16,164

Notes: Table contains summary statistics of main variables. See text for the construction of the occupational skill measures (Section III) and the returns-to-skills measures (Section VII). *Rural status* is a dummy variable taking the value 1 if persons lives in a locality with less than 2,500 inhabitants (0 otherwise). Observations are weighted by sampling weights. *Data sources:* ENOE, ENET, MMP, MxFLS, Mexican CONOCER, and U.S. O*NET.

Table D2: Range of Occupational Skills in Main SINCO Categories

	(1)	(2)	(3)
Occupations	Range		Share
	Cognitive	Manual	
1–digit level			
Officials, directors, and chiefs	0.718	0.420	0.044
Professionals and technicians	0.877	0.583	0.143
Auxiliary workers in administrative activities	0.742	0.453	0.044
Traders, sales clerks, and sales agents	0.579	0.180	0.100
Workers in personal services and surveillance	0.985	0.544	0.069
Workers in agriculture, livestock, forestry, hunting, and fishing	0.397	0.518	0.159
Craft workers	0.951	0.560	0.131
Operators of industrial machinery, assemblers, and drivers	0.733	0.397	0.126
Workers in elementary and supportive activities	0.353	0.507	0.184
Average	0.661	0.476	
2–digit level			
Average	0.430	0.335	
3–digit level			
Average	0.210	0.173	

Notes: Table shows ranges of occupational skills calculated by subtracting the minimum occupational score from the maximum occupational score within each occupation. *Share* is the fraction of individuals working in the respective occupation. Averages reported in the bottom of each occupational level denote the average skill range of all occupations in the respective level weighted by the occupation's share. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

D Mexican and U.S. Census Data

Mexican Census

We use data from the 2000 Mexican Census to construct returns on basic and occupational skills for Mexican residents (see Section V and Appendix F). The 2000 Mexican Census is a 10.6% random sample of the Mexican population and is taken from the Integrated Public Use Microdata Series (IPUMS) International database (Minnesota Population Center, 2015) and is provided by the Mexican National Institute of Statistics, Geography, and Informatics. The sample consists of males aged 16 to 65 years, who are not in school and were born in Mexico. Earnings are expressed in log hourly earnings in constant, PPP-adjusted 2010 U.S. dollars. The construction of hourly earnings follows Chiquiar and Hanson (2005, footnote 11): We use monthly labor income divided by 4.5 times the hours worked last week. To obtain real hourly earnings in 2010 U.S. dollars, we convert Mexican earnings to U.S. dollars using the PPP-adjusted exchange rate from 2000 (6.093605 Mexican pesos per U.S. dollar; see OECD (2016a, PPP for GDP)) and express those earnings in 2010 values by using U.S. CPI data from the U.S. Bureau of Labor Statistics (Consumer Price Index—All Urban Consumers, annual averages, series CUUR0000SA0, U.S. city average, all items, not seasonally adjusted). We drop the top and bottom 0.5% of earnings observations to eliminate outliers and restrict the sample to those who have reported working between 20 and

84 hours per week (Chiquiar and Hanson, 2005; Fernández-Huertas Moraga, 2011). In robustness checks, we also use data from the 2010 Mexican Census, applying the same sample restrictions and variable definitions as for the 2000 Mexican Census. Here, Mexican earnings are converted to U.S. dollars using the PPP-adjusted exchange rate from 2010 (7.667777 Mexican pesos per U.S. dollar; see OECD (2016a, PPP for GDP)).

U.S. Census and American Community Survey (ACS)

To construct returns on basic and occupational skills for recent Mexican migrants in the United States (see Section V and Appendix F), we use data from the 2000 U.S. Census. This is a 5% random sample of the U.S. population and is taken from the IPUMS USA database (Ruggles et al., 2015). The sample contains males aged between 16 and 65 years who are not currently enrolled in school. Earnings are expressed in log hourly earnings in constant 2010 U.S. dollars. The construction of hourly wages follows Chiquiar and Hanson (2005, footnote 11) in using annual labor income divided by the product of weeks worked last year and usual hours worked per week. To obtain real hourly earnings in 2010 U.S. dollars, we use U.S. CPI data from the U.S. Bureau of Labor Statistics (Consumer Price Index—All Urban Consumers, annual averages, series CUUR0000SA0, U.S. city average, all items, not seasonally adjusted). We drop the top and bottom 0.5% of wage observations to eliminate outliers and restrict the sample to those who have reported working between 20 and 84 hours per week (Chiquiar and Hanson, 2005; Fernández-Huertas Moraga, 2011). In robustness checks, we also use data from the 2010 U.S. American Community Survey (ACS), applying the same sample restrictions and variable definitions as for the 2000 U.S. Census. In main analysis, we restrict the data to recent Mexican migrants in the United States, defined as migrants that have migrated to the United States between 1990 and 2000 (2000 U.S. Census) and between 2000 and 2010 (2010 ACS), respectively. We exclude migrants to the United States below an age of 16 years at time of arrival. Note that in the U.S. Census earnings and occupations are imputed for some of the respondents. Appendix F shows that these imputations do not matter for the return calculations.

E Model Appendix

A Occupational Selection on Comparative Advantage

In this section, we discuss how our model generalizes when workers choose occupations based on *comparative advantage* (Acemoglu and Autor, 2011). We show that these changes do not affect the baseline model predictions.

In the original Roy model, the individual chooses between job 1 and job 2 based on random productivity draws u_1 and u_2. If $u_1 > u_2$, then job 1 is chosen. In our model, u is a function of a vector of skills $\mathbf{z}$. Skills are only productive when they are combined with tasks of a specific job (skills alone do not produce value). A worker therefore chooses a job according to $\max\{u_1(\mathbf{z}), u_2(\mathbf{z}), ..., u_k(\mathbf{z})\}$ among all k jobs where each job i uses skills differently. Thus, comparative advantage still holds in terms of $u(\mathbf{z})$. We move on to characterize $u_i(\mathbf{z})$ by assuming that there are n skills and that every job represents a collection of tasks that use these skills according to technology-determined levels of intensity. We take both technology and occupations as exogenously given.

The marginal productivity of a worker with skills $\mathbf{z}$ in a job $\mathbf{x}$ consists of two parts: (1) the (absolute) level of skill and (2) quality of the match of skills to what the job requires. Assume that:

$$u(\mathbf{x}, \mathbf{z}) = r(\mathbf{x}, \mathbf{z})m(\mathbf{x}, \mathbf{z}), \tag{E1}$$

where $r : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ is the skill rent attributed to an endowment of skill $z \in \mathbb{R}^n$(which in equilibrium depends on occupation-independent prices) and $m : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}_+$ is the match quality function. For example, a highly skilled individual (with large values of z_i) is well-matched to an occupation that is described by large values of x_i. This highly skilled individual, however, cannot be very productive in an occupation where job requirements $\mathbf{x}$ are low. In this case, the value of m would be large, but the value of r would be small.

In equilibrium, skills are valued equally across all jobs and there are no trade-offs between occupation-specific wages and match quality. We therefore write:

$$u(\mathbf{x}, \mathbf{z}) = r(\mathbf{x}, \mathbf{z})m(\mathbf{x}, \mathbf{z}) = \upsilon(\mathbf{z})\phi(\mathbf{x}, \mathbf{z}), \tag{E2}$$

where $\upsilon : \mathbb{R}^n \to \mathbb{R}$ is an occupation-independent skill valuation and $\phi : \mathbb{R}^n \times \mathbb{R}^n \to [0, 1]$ is a match quality function *relative* to the best use of skills $\mathbf{z}$. Thus, $\phi = 1$ signals that task requirements and worker skills are optimally matched. For $\phi < 1$, the match is not optimal. In the extreme with $\phi = 0$, the worker is unable to fulfill the job requirements and therefore does not receive any rewards from working in the occupation. For analytical convenience, we assume that ϕ is a continuous and differentiable function that achieves the unique maximum of 1 when $\mathbf{x} = \mathbf{z}$

(perfect match). The gradient of the contour of ϕ can be used to measure the match quality rate of transformation of one skill for another. This means that the abundance of one skill can compensate for the lack of another.

For $\upsilon(\mathbf{z})$, we assume $\log \upsilon(\mathbf{z}) = \mathbf{p}'\mathbf{z}$, where $\mathbf{p}$ is the vector of skill prices (Autor and Handel, 2013). When all workers are perfectly matched, $u(\mathbf{x}, \mathbf{z}) = \upsilon(\mathbf{z})$ because the match quality is $\phi = 1$. Under the assumptions stated, maximizing wages is equivalent to maximizing match quality because $\upsilon(\mathbf{z})$ is independent of $\mathbf{x}$. Hence, occupational selection on comparative advantage is equivalent to choosing a job with the highest wage as jointly determined by the requirements of a job (task intensity) and the skills of the worker. When there is a finite number of jobs and subject to mean-zero noise in the measurement of skills, all the results on migrant selection from the model in Section III.A generally hold because the basic mechanism how workers choose their occupations, that is, by income maximization, is not affected.

B Proof of Selection Equation

Let Y_1 and Y_2 be random variables given by $Y_1 = Z_1$ and $Y_2 = \lambda_1 Z_1 + \lambda_2 Z_2 - \kappa$. The linear projection of Y_1 on Y_2 is:

(E3)
$$\begin{aligned} Y_1 &= \mu_1 + \frac{\operatorname{Cov}(Y_1, Y_2)}{\operatorname{Var}(Y_2)}(Y_2 - \mathbb{E}[Y_2]) + \eta \\ &= \mu_1 + (\lambda_1 + \beta_{21}\lambda_2)\frac{\sigma_1^2}{\sigma^2}(Y_2 - \mathbb{E}[Y_2]) + \eta, \end{aligned}$$

where η is the error term which is uncorrelated with Y_2 by construction. Then,

(E4)
$$\mathbb{E}[Y_1|Y_2 > 0] = \mu_1 + (\lambda_1 + \beta_{21}\lambda_2)\frac{\sigma_1^2}{\sigma^2}\,\mathbb{E}[(Y_2 - \mathbb{E}\,Y_2)|Y_2 > 0].$$

Since $\mathbb{E}\,Y_2 = \lambda_1\mu_1 + \lambda_2\mu_2 - \kappa$,

(E5)
$$\begin{aligned} \mathbb{E}[(Y_2 - \mathbb{E}\,Y_2)|Y_2 > 0] &= \sigma\,\mathbb{E}\left[\frac{Y_2 - \mathbb{E}\,Y_2}{\sigma}\middle|\frac{Y_2 - \mathbb{E}\,Y_2}{\sigma} > -\frac{\mathbb{E}\,Y_2}{\sigma}\right] \\ &= \sigma\frac{\phi(d)}{1 - \Phi(d)}, \end{aligned}$$

where we use the fact that if $X \sim N(0,1)$, then $\mathbb{E}[X|X > c] = \phi(c)/[1 - \Phi(c)]$. Combining the results, we obtain the analog of Equation 4 as:

(E6)
$$\mathbb{E}[Y_1|Y_2 > 0] = \mu_1 + (\lambda_1 + \beta_{21}\lambda_2)\frac{\sigma_1^2}{\sigma}\frac{\phi(d)}{1 - \Phi(d)}.$$

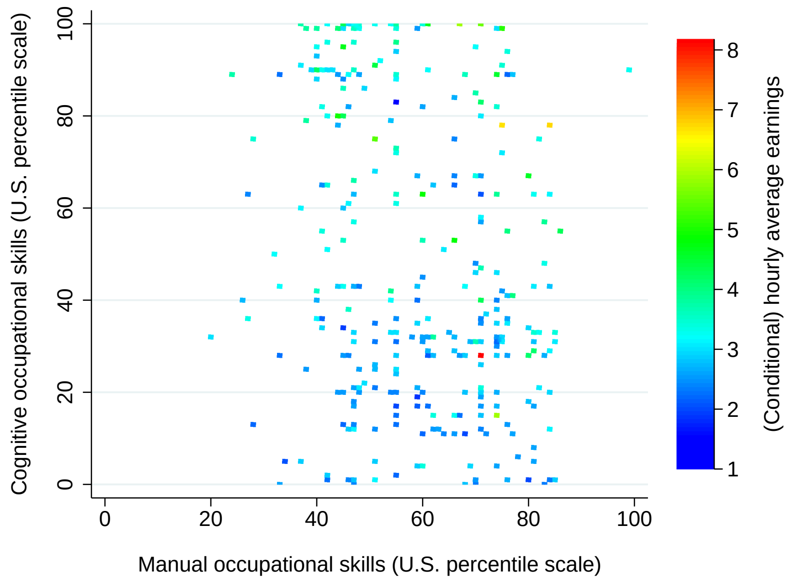
F Returns to Occupational Skills

The model specified in Section III.A predicts that the main drivers of Mexican emigrant selection are the differential returns to occupational skills between Mexico and the United States. To test this prediction, we estimate returns to occupational skills from Mincer-type earnings regressions for Mexican residents and recent Mexican immigrants in the United States (Ambrosini and Peri, 2012; Kaestner and Malamud, 2014). Appendix D.D provides details on the Census data and the sample construction.

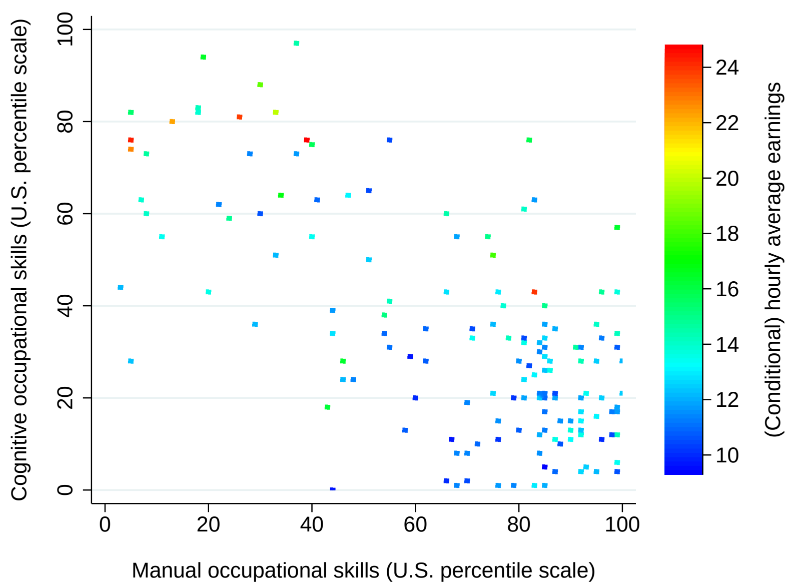
We begin by providing visual evidence on the distribution of hourly earnings (conditional on control variables) by skill percentiles for Mexicans in the 2000 Mexican Census (Figure F1(a)) and for the recent Mexican migrants in the 2000 U.S. Census (Figure F1(b)). The figures aid our understanding of the earnings situation of Mexican residents and recent Mexican migrants in the United States in several ways. First, as expected, the average wage level (expressed in purchasing power parities) is higher in the United States than in Mexico. Second, most Mexican workers in the United States cluster in high-manual, low-cognitive occupations. Interestingly, most of them work in occupations that require manual skills above the 80th percentile of manual skills—a percentile that does not even exist in Mexico. In contrast, Mexican migrants in the United States typically do not work in occupations requiring high levels of cognitive skills, even though there are Mexican residents who do work in such occupations in Mexico. Third, in both countries, hourly wages increase strongly with cognitive skills, while the pattern is less clear for manual skills.

Figure F1: Average Hourly Earnings in the Year 2000 by Skill Percentiles

(a) Mexican Residents



(b) Recent Mexican Migrants



Notes: Figures show average hourly earnings by skill percentiles for Mexican residents (Figure F1(a)) and for Mexican migrants in the United States who immigrated between 1990 and 2000 (Figure F1(b)). Sample consists of males aged 16–65. Earnings are expressed in constant 2010 U.S. dollars. For Mexico, earnings are adjusted for PPP. Hourly earnings are conditional on education (five categories), age (six categories), marital status, urban (metro status for the United States), and state fixed effects. Cells with less than 20 observations are dropped. *Data sources:* 2000 Mexican Census (Figure F1(a)), 2000 U.S. Census (Figure F1(b)), Mexican CONOCER, and U.S. O*NET.

It is important to note that returns to specific tasks or skills are not easily retrieved from Mincer-type earnings models because the tasks that a worker performs on the job are a bundle of activities that require multiple skills to be carried out (Heckman and Scheinkman, 1987; Autor and Handel, 2013). However, to provide intuition regarding the model's predictions in the context of Mexico-to-U.S. migration, we follow the common approach in the literature to estimate returns to a particular domain of skills in a Mincer-type framework (e.g., Autor and Handel, 2013; Hanushek et al., 2015), holding constant the other skill domain(s). More specifically, separately for each skill domain (i.e., cognitive or manual skills), we regress log hourly earnings on this skill domain and control flexibly for the other domain by including skill decile fixed effects. The resulting returns-to-skills estimate is to be interpreted as the average return over the entire distribution of the other skill. For comparison, we also estimate models that include cognitive and manual skills linearly. Importantly, when we assess the role of differential returns to skills for the migration decision and the selection on earnings (Section V), we account for the fact that workers are rewarded for applying bundles of skills by slicing the cognitive and manual skill distributions into cells and calculating returns within these cells.

Tables F1 and F2 show the results of the earnings regressions for the 2000 Mexican and U.S. Census, respectively. All specifications control for years of completed education (five categories), age (six categories), martial status, urban status, and state of residence. For Mexican residents, returns to manual skills are statistically insignificant and very small (Table F1, Column 2). A one-decile increase in manual skills is associated with 0.04% lower hourly earnings. This is not implausible given that the supply of manual skills is very large in Mexico (see also Figure 1).[16] Recent Mexican migrants in the United States have considerably larger returns to manual skills than Mexican residents. They receive 2.3% higher hourly earnings for an increase of one decile in manual skills (Table F2, Column 2).[17] For cognitive skills, we find the opposite picture. Returns are higher for Mexican residents in Mexico (5.1%; Table F1, Column 3) than for recent Mexican migrants (4.1%; Table F2, Column 3). Given these differences in the returns, the Roy/Borjas model developed in Section III.A predicts that Mexican migrants are positively selected on manual skills and negatively selected on cognitive skills.[18]

For comparison, Columns 4–6 of Table F2 provide return estimates based on the 2010 ACS instead of the 2000 U.S. Census. Returns are generally slightly higher. However, returns to cognitive skills for Mexican migrants are still higher in Mexico than in the United States, so the model predictions remain unchanged.

[16] Other interpretations are possible, including unobserved negative selection of low-ability workers into occupations that are intensive in manual tasks (see Autor and Handel, 2013, for further explanations for negative estimated returns to manual tasks).

[17] The fact that manual skills are a significant predictor of wages in the United States provides prima facie evidence that our manual skill measure is likely to be informative about job content rather than simply picking up noise.

[18] Notice that negative skill prices—as empirically the case for manual skills in Mexico—do not alter the model predictions regarding the implications of differential returns to skills for migration.

To put the estimated returns for recent Mexican migrants into perspective, Table F2 provides return estimates for Mexicans who migrated before 1990 (Columns 1 to 3 of Panel B) and before 2000 (Columns 4 to 6 of Panel B), non-Mexican migrants (Panel C), and for natives (Panel D). Returns to occupational skills for less recent Mexican migrants, are quite similar to those of their recent counterparts. In particular, the largest returns to cognitive skills for earlier migrants (4.8%) still do not exceed those earned in Mexico. Natives exhibit rather low returns from manual skills (0.2%) and rather high returns from cognitive skills (5.7%). This may be the result of skill specialization driven by comparative advantage of Mexicans in manual-skill-intensive occupations (Peri and Sparber, 2009; Peri, 2012). For other migrants, we document very low returns to manual skills (0.6%), but very high returns to cognitive skills (7.3%). One potential explanation for this finding is the rather restrictive U.S. immigration policy that permits residence and work visas mainly to high-skilled migrants (e.g., via the H1B visa program).

In our sample in the 2000 U.S. Census, we observe that 32% of male Mexican migrants have imputed wages and 20% have imputed occupations; for 15% of the migrants, both variables are imputed. The numbers are similar for the 2010 ACS. Imputation involves assigning a respondent with missing values the information on wages and/or occupation from another observationally similar respondent ("donor"). Borjas (2014) notes that the imputation algorithm does not use immigration status to identify the donors. Hence, for a large part of our sample, native workers' information is used to impute missing values for Mexican migrants. This imputation procedure may result in an upward bias in the wages of Mexican migrants, which may distort the estimated returns to cognitive and manual skills. In Tables F3 and F4, we provide Mincer regressions for recent Mexican migrants in the United States when we exclude observations with imputed earnings and/or occupations. The results are very similar to the baseline results.[19]

[19] When calculating differential returns in Section V, the exclusion of Mexican migrants with imputed values leads to slightly larger coefficients for the differential returns (from 0.242 to 0.382 for basic returns and from 1.497 to 1.553 for occupational returns). This is most likely due to reduced measurement error.

Table F1: Returns to Occupational Skills in Mexico

	(1)	(2)	(3)
Dependent variable: log hourly earnings			
Manual skills	0.0011*	–0.0004	
	(0.0006)	(0.0006)	
Cognitive skills	0.0475***		0.0510***
	(0.0003)		(0.0004)
Control variables	x	x	x
Cognitive skill decile fixed effects		x	
Manual skill decile fixed effects			x
R-squared	0.432	0.438	0.439
Median manual skills = 0.605, median cognitive skills = 0.284.			

Notes: Table shows returns to cognitive and manual occupational skills in the Mexican Census 2000. Sample restricted to Mexican-born males aged 16–65 who are not in school and work between 20 and 84 hours per week. Dependent variable is log hourly earnings, constructed by dividing monthly earnings by $4.5\times$ hours worked per week. The largest and smallest 0.5% of hourly earnings are dropped. Cognitive and manual skills are based on the occupation held when the Mexican Census was conducted. Skill measures are scaled by 10 to allow for interpretation in decile changes and are denoted in 2010 U.S. deciles. All regressions condition on a full set of control variables: education (five categories), age (six categories), marital status, state-of-living fixed effects, and urban status. Columns 2 and 3 contain decile fixed effects of cognitive skills (Column 2) and of manual skills (Column 3). Decile cutoffs are taken from the occupational skill distribution in the Mexican Census 2000. $N = 1,424,024$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p$<$0.01, ** p$<$0.05, * p$<$0.1. *Data sources:* 2000 Mexican Census (10.6% sample), Mexican CONOCER, and U.S. O*NET.

Table F2: Returns to Occupational Skills in the United States

	(1)	(2)	(3)	(4)	(5)	(6)
	U.S. Census 2000			ACS 2010		
Panel A: Recent Mexican migrants						
Dependent variable: log hourly earnings						
Manual skills	0.0157***	0.0233***		0.0236***	0.0339***	
	(0.0020)	(0.0021)		(0.0047)	(0.0051)	
Cognitive skills	0.0546***		0.0406***	0.0704***		0.0437***
	(0.0022)		(0.0024)	(0.0057)		(0.0068)
R-squared	0.078	0.087	0.086	0.118	0.130	0.133
	$N = 57,370$, median manual skills = 0.854, median cognitive skills = 0.150.			$N = 8,586$, median manual skills = 0.868, median cognitive skills = 0.128.		
Panel B: Other Mexican migrants						
Dependent variable: log hourly earnings						
Manual skills	0.0230***	0.0276***		0.0247***	0.0287***	
	(0.0018)	(0.0019)		(0.0038)	(0.0041)	
Cognitive skills	0.0616***		0.0475***	0.0640***		0.0423***
	(0.0019)		(0.0020)	(0.0039)		(0.0043)
R-squared	0.089	0.097	0.098	0.088	0.102	0.105
	$N = 57,847$, median manual skills = 0.854, median cognitive skills = 0.187.			$N = 15,372$, median manual skills = 0.854, median cognitive skills = 0.150.		
Panel C: Other migrants						
Dependent variable: log hourly earnings						
Manual skills	0.0002	0.0064***		-0.0007	0.0074***	
	(0.0008)	(0.0009)		(0.0017)	(0.0018)	
Cognitive skills	0.0889***		0.0732***	0.1037***		0.0859***
	(0.0009)		(0.0010)	(0.0018)		(0.0020)
R-squared	0.274	0.288	0.291	0.344	0.366	0.368
	$N = 210,043$, median manual skills = 0.617, median cognitive skills = 0.401.			$N = 51,624$, median manual skills = 0.617, median cognitive skills = 0.390.		
Panel D: Natives						
Dependent variable: log hourly earnings						
Manual skills	0.0007***	0.0017***		0.0032***	0.0058***	
	(0.0002)	(0.0002)		(0.0005)	(0.0006)	
Cognitive skills	0.0598***		0.0569***	0.0714***		0.0668***
	(0.0002)		(0.0003)	(0.0006)		(0.0006)
R-squared	0.289	0.292	0.300	0.315	0.321	0.328
	$N = 2,487,894$, median manual skills = 0.659, median cognitive skills = 0.427.			$N = 493,380$, median manual skills = 0.594, median cognitive skills = 0.430.		
Control variables	x	x	x	x	x	x
Cognitive skill decile fixed effects		x			x	
Manual skill decile fixed effects			x			x

Notes: Table shows returns to cognitive and manual occupational skills in the 2000 U.S. Census (Columns 1–3) and in the 2010 U.S. ACS (Columns 4–6). Sample restricted to males aged 16–65 who are not in school and work between 20 and 84 hours per week. Dependent variable is log hourly earnings, constructed by dividing yearly earnings by weeks worked $\times$ hours worked per week. The largest and smallest 0.5% of hourly earnings are dropped. Cognitive and manual skills are based on the occupation held when the respective census was conducted. Skill measures are scaled by 10 to allow for interpretation in decile changes and are denoted in 2010 U.S. deciles. *Recent Mexican migrants* are those who migrated to the United States between 1990 and 2000 (Columns 1–3) or between 2000 and 2010 (Columns 4–6). *Other Mexican migrants* are those who migrated before 1990 (Columns 1–3) or before 2000 (Columns 4–6). *Other migrants* are non-Mexican migrants. We exclude migrants to the United States below an age of 16 years at time of arrival. *Natives* are those born in the United States. All regressions condition on a full set of control variables: education (five categories), age (six categories), marital status, state-of-living fixed effects, and metropolitan area status. Columns 2, 3, 5, and 6 contain decile fixed effects of cognitive skills (Columns 2 and 5) and of manual skills (Columns 3 and 6). Decile cutoffs are taken from the occupational skill distribution in the Mexican Census 2000. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data sources:* 2000 U.S. Census (5% sample), 2010 U.S. ACS (1% sample), Mexican CONOCER, and U.S. O*NET.

Table F3: Returns to Occupational Skills in the United States:
Results With vs. Without Imputations for Earnings

	(1)	(2)	(3)	(4)	(5)	(6)
	With imputations (baseline)			Without imputed earnings		
Dependent variable: log hourly earnings						
Manual skills	0.0157***	0.0233***		0.0171***	0.0249***	
	(0.0020)	(0.0021)		(0.0024)	(0.0024)	
Cognitive skills	0.0546***		0.0406***	0.0557***		0.0416***
	(0.0022)		(0.0024)	(0.0027)		(0.0030)
Control variables	x	x	x	x	x	x
Cognitive skill decile fixed effects		x			x	
Manual skill decile fixed effects			x			x
R-squared	0.078	0.087	0.086	0.087	0.096	0.094
	$N = 57,370$; median manual skills = 0.854, median cognitive skills = 0.150.			$N = 35,373$; median manual skills = 0.854, median cognitive skills = 0.150.		

Notes: Table shows returns to cognitive and manual occupational skills in the 2000 U.S. Census for recent Mexican migrants who migrated to the United States between 1990 and 2000. All regressions condition on a full set of control variables: education (five categories), age (six categories), marital status, state-of-living fixed effects, and metropolitan area status. Columns (2) and (5) contain decile fixed effects of cognitive skills, and Columns (3) and (6) contain decile fixed effects of manual skills. Decile cutoffs are taken from the occupational skill distribution in the Mexican Census 2000. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* 2000 U.S. Census (5% sample), Mexican CONOCER, and U.S. O*NET.

Table F4: Returns to Occupational Skills in the United States:
Results Without Imputations for Occupations and Earnings

	(1)	(2)	(3)	(4)	(5)	(6)
	Without imputed occupations			Without imputed occupations and without imputed earnings		
Dependent variable: log hourly earnings						
Manual skills	0.0143***	0.0235***		0.0158***	0.0246***	
	(0.0023)	(0.0023)		(0.0026)	(0.0026)	
Cognitive skills	0.0501***		0.0358***	0.0562***		0.0407***
	(0.0025)		(0.0028)	(0.0028)		(0.0032)
Control variables	x	x	x	x	x	x
Cognitive skill decile fixed effects		x			x	
Manual skill decile fixed effects			x			x
R-squared	0.078	0.087	0.086	0.092	0.104	0.101
	$N = 45,292$; median manual skills = 0.867, median cognitive skills = 0.133.			$N = 33,041$; median manual skills = 0.865, median cognitive skills = 0.150.		

Notes: Table shows returns to cognitive and manual occupational skills in the 2000 U.S. Census for recent Mexican migrants who migrated to the United States between 1990 and 2000. All regressions condition on a full set of control variables: education (five categories), age (six categories), marital status, state-of-living fixed effects, and metropolitan area status. Columns (2) and (5) contain decile fixed effects of cognitive skills, and Columns (3) and (6) contain decile fixed effects of manual skills. Decile cutoffs are taken from the occupational skill distribution in the Mexican Census 2000. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* 2000 U.S. Census (5% sample), Mexican CONOCER, and U.S. O*NET.

G Robustness of the Results on Emigrant Selection on Occupational Skills

This section checks the robustness of our main results on emigrant selection on occupational skills. We also investigate the persistence of selection on occupational skills.

A Relaxing the Assumption of Risk Neutrality of Migrants

As outlined in Section III.A, we assume in the theoretical model that migrants are risk neutral. Below, we discuss how the pattern of selection would be affected when modeling migrants' risk preferences more realistically.

Consider two risk-averse Mexicans with an identical pre-migration wage but with different skill bundles who are considering the option of migrating to the United States. The propensity to migrate will be higher for the worker that has a larger endowment of manual skills, if (a) the transferability of cognitive skills takes more time than the transferability of manual skill and/or (b) the dispersion of earnings in the United States is larger for individuals with a comparative advantage in cognitive skills.[20] This would induce a pattern of negative selection on cognitive skills even if the monetary return to the two skills was the same in both countries. While this would suggest that the migration returns we use in the analysis do not correctly reflect the expected returns (in particular, for Mexicans with high cognitive skills), it would not invalidate the returns-based explanation for selection. Mexicans would still base their migration decision on a comparison of returns to their skills at home and abroad, but they would consider different (i.e., risk-adjusted) returns than those we can observe in the data.

There is also evidence that the characterization of migrants as generally being equally risk averse as an average individual in the population is not necessarily realistic. In fact, the existing literature suggests that migrants are generally *less* risk averse than non-migrants (Jaeger et al., 2010; Gibson and McKenzie, 2011; Bryan et al., 2014; Dustmann et al., 2017). Moreover, Parey et al. (2017) show that more able migrants are attracted by (and not discouraged from) a higher wage dispersion in the destination country, which is consistent with migrants being less risk-averse than the average non-migrant (or even risk-seeking). Furthermore, an empirical result that is at odds with the idea that workers with high cognitive skills discount the expected returns to their skills by more than workers with high manual skills do is that more education (which also increases the likelihood of working in cognitive-intense occupations) is usually associated with higher migration probability

[20]The evidence indeed suggests that the dispersion of earnings in occupations with a comparative advantage in cognitive skills is larger than in occupations with a comparative advantage in manual skills. In the 2000 U.S. Census, the standard deviation of log hourly earnings is 0.67 (0.54) for recent Mexican migrants with a comparative advantage in cognitive (manual) skills. The dispersion of earnings is very similar for U.S. natives (standard deviation of 0.69 (0.59) for workers with a comparative advantage in cognitive (manual) skills). We continue to find a larger dispersion of earnings for workers with a comparative advantage in cognitive skills when controlling for education and a quadratic polynomial in age.

(Grogger and Hanson, 2011). If migrants were indeed risk-seeking, those with a comparative advantage in cognitive skills may even have returns expectations larger than those we can observe in the data. This would imply that the importance of returns to skills for migration suggested by our results is even attenuated. Thus, it is not entirely clear how a more realistic depiction of Mexican workers' risk preferences would affect our conclusions about the role of returns to skills for (selective) migration.

B Robustness across Datasets and Specifications

Table G1 shows the results of our baseline models using data from MxFLS.We find that both the pattern of selection on occupational skills and the vanishing negative selection on education once occupational skills are accounted for is consistent across time periods and sampling frames. Moreover, the results also indicate that the likely undercount of migrants in ENOE due to whole-household migration is unlikely to affect our baseline results.

Because they contain information on migrants' entire work history, the MMP data permit checking whether the ENOE results presented in Section IV are specific to recent migration episodes and whether the limited time coverage (e.g., left-censored occupational histories) potentially confounds the results. Table G2 reports the results for the MMP-based analysis. Columns 1 to 4 replicate the baseline models from Table 2, but use workers' full pre-migration occupational history to construct cognitive and manual skills. Corroborating the descriptive results in Table A1, the selection pattern is remarkably similar in MMP and ENOE. Just as in our main results, we also observe that the selection on education becomes considerably weaker once we include occupational skills. The results are robust to a number of additional analyses exploiting specific features of the MMP data. In Column 5 (Column 6), our measures of cognitive and manual skills are constructed using only the first (last) pre-migration occupation instead of using the job content of all occupations held prior to migration. Column 7 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.

Finally, Table G3 shows that the results also hold when using data from ENET, which covers the time period between 2000 and 2004.

The selection pattern holds across a range of robustness specifications (results not shown). First, we include education (five categories) and age (six categories) as categorical variables to allow for intermediate selection on these variables. Second, we control for the distance to the U.S. border as a proxy for the cost of migration. Third, we drop the largest Mexican occupation, agricultural workers, or even the three largest three-digit occupations (which constitute one-quarter of the sample). Fourth, we estimate probit models, which yield marginal effects very similar to those from the linear probability model.

Table G1: Emigrant Selection on Occupational Skills: Results from MxFLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: migration propensity to the U.S.								
					Round 1	First occ	Last occ	Within state
Cognitive skills	–0.048	–0.125***		–0.100*	–0.110*	–0.069	–0.119**	–0.092*
	(0.030)	(0.046)		(0.053)	(0.057)	(0.059)	(0.048)	(0.054)
Manual skills	0.323***	0.196**		0.294***	0.243**	0.236***	0.169**	0.261***
	(0.085)	(0.088)		(0.091)	(0.104)	(0.087)	(0.085)	(0.091)
Cognitive skills × manual skills		–0.061*		–0.077**	–0.080**	–0.062*	–0.085**	–0.058*
		(0.032)		(0.032)	(0.033)	(0.032)	(0.034)	(0.033)
Years of schooling			–0.071***	–0.010	–0.003	–0.028	–0.037**	0.005
			(0.013)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)
Age			–0.046***	–0.045***	–0.043***	–0.048***	–0.050***	–0.042***
			(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.005)
Residence state fixed effects								x
Observations	16,164	16,164	16,164	16,164	7,909	15,695	12,591	16,163

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by yearly migrant share. Average yearly migration rate is equal to 2.50%. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of the current occupation, the occupation five years prior to the survey, and the occupation at labor-market entry. Skill measures are demeaned and scaled by 10. In Column 5, only participants of round 1 of the MxFLS survey are included in the estimation sample. In Column 6, we use the occupation at labor-market entry to calculate occupational skill measures; people without information on the first occupation are dropped. 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. All regressions contain survey-year fixed effects. Observations are unweighted. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data sources:* MxFLS, Mexican CONOCER, and U.S. O*NET.

Table G2: Emigrant Selection on Occupational Skills: Results from MMP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: migration propensity to the U.S.							
					First occ	Last occ	Within state
Cognitive skills	–0.097***	–0.132***		–0.128***	–0.130***	–0.125***	–0.147***
	(0.010)	(0.013)		(0.015)	(0.014)	(0.012)	(0.015)
Manual skills	0.069***	0.057***		0.087***	0.061***	0.087***	0.085***
	(0.022)	(0.021)		(0.021)	(0.020)	(0.018)	(0.021)
Cognitive skills × manual skills		–0.021***		–0.030***	–0.041***	–0.049***	–0.027***
		(0.005)		(0.005)	(0.006)	(0.005)	(0.006)
Years of schooling			–0.059***	–0.017**	–0.025***	–0.019***	–0.003
			(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
Age			–0.046***	–0.043***	–0.045***	–0.042***	–0.046***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Birth state fixed effects							x
Observations	471,123	471,123	471,123	471,123	471,123	410,789	470,659

Notes: Sample includes Mexican males aged 16 to 65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by sample-specific annual migrant share. Average yearly migration rate is equal to 2.4%. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations prior to migration. Skill measures are demeaned and scaled by 10. In Column 5, we use the occupation at labor-market entry to calculate occupational skill measures. In Column 6, we consider only the last pre-migration occupation to calculate occupational skill measures; people without occupational information immediately before migration are dropped. All regressions contain year fixed effects. Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the individual level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data sources:* MMP, Mexican CONOCER, and U.S. O*NET.

Table G3: Emigrant Selection on Occupational Skills: Results from ENET

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: migration propensity to the U.S.							
Cognitive skills	–0.137***	–0.167***		–0.161***	–0.148***	–0.098***	–0.110***
	(0.005)	(0.006)		(0.007)	(0.007)	(0.007)	(0.015)
Manual skills	0.204***	0.183***		0.187***	0.168***	0.125***	0.109***
	(0.013)	(0.013)		(0.013)	(0.013)	(0.014)	(0.024)
Cognitive skills × manual skills		–0.063***		–0.069***	–0.064***	–0.036***	–0.024***
		(0.004)		(0.004)	(0.004)	(0.004)	(0.007)
Years of schooling			–0.062***	–0.003	0.004	0.011***	0.000
			(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Age			–0.039***	–0.036***	–0.036***	–0.038***	–0.039***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed Effects							
Birth-by-residence state [1,209]					x		
Municipality [1,204]						x	
Occupation [143]							x

Notes: Table shows specifications analogous to those in Table 2 using ENET data. Sample restrictions and variable definitions are the same as in Table 2. Average yearly (quarterly) migration rate is equal to 2.72% (0.68%). All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,069,926$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENET, Mexican CONOCER, and U.S. O*NET.

C Long-Run Dynamics of Selection on Occupational Skills

During the last 15 years, Mexico has experienced very different emigration waves that were partly driven by changing economic conditions in Mexico and the United States (Hanson and McIntosh, 2010; Villarreal, 2014). The Mexican-born population in the United States 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 fell 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 and the size of the migrant community in the United States.

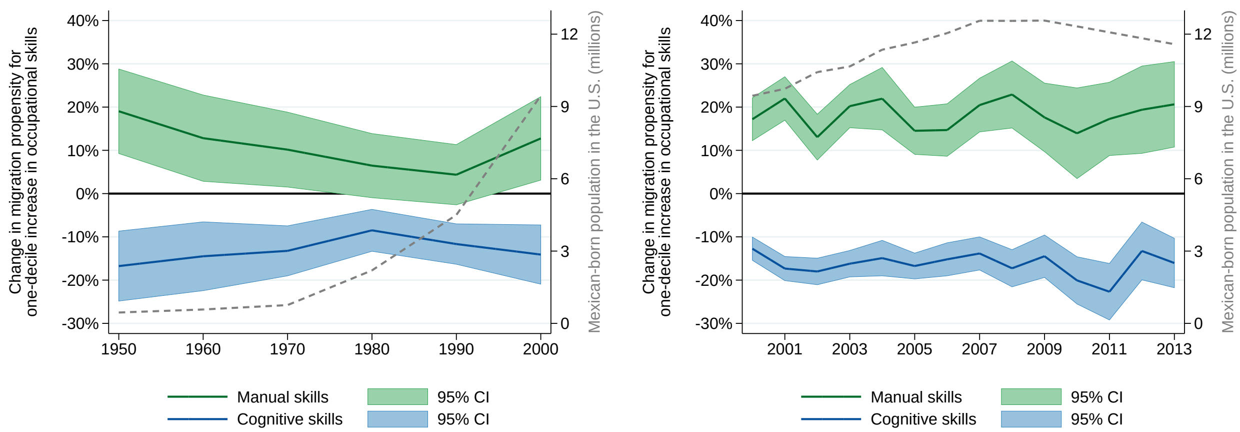
Pooling data from ENET and ENOE, the right panel of Figure G1 plots the annual migration propensity for a one-decile increase in cognitive (blue line) and manual (green line) skills in the period 2000–2013.[21] Remarkably, we observe that Mexican emigrants have been positively selected on manual skills and negatively selected on cognitive skills over the entire period. Notably, this pattern also holds during the recent decline in Mexican emigration.

One might wonder whether the selection pattern changes when considering earlier periods, when the Mexican community in the United States was smaller and different U.S. immigration policy regimes prevailed (see also Appendix I.A). The left panel of Figure G1 shows that even though the Mexican migrant community in the United States in the 1950s, 1960s, and most of

[21] Estimates are based on the model in Column 4 of Table 2.

the 1970s was very small, the pattern of selection of Mexican emigrants on occupational skills was remarkably persistent. This is also true for the period from 1970 to 2000, when the United States experienced a sharp increase in the Mexican-born population from almost zero to around 9 million.[22]

Figure G1: Emigrant Selection Over Time



Notes: Figures show the change in migration propensity for a one-decile increase in occupational skills (left scale) and the Mexican-born population in the United States (right scale). Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations (in MMP, we can observe the entire pre-migration history; in ENET/ENOE, we can observe up to four pre-migration quarters). *Data sources:* MMP (left figure), ENET/ENOE (right figure), Mexican CONOCER, and U.S. O*NET.

[22]Estimates are based on MMP data. All years within a decade are pooled to increase sample size.

H Robustness of the Results on Differential Returns to Occupational Skills

It is important to acknowledge the inherent selection bias associated with the simple calculations of the labor-market returns presented in Section V. Thus, we do not claim that our estimated differential returns are causal. Tackling endogeneity in the returns estimation is extremely challenging because many studies—including our own—document that Mexican migrants to the United States are selected. However, our results on the role of differential returns to occupational skills for emigrant selection are unlikely to be explained by migrant selectivity for a number of reasons. First, following Kaestner and Malamud (2014), we use Heckman's 1979 two step estimator to address sample selection of Mexican migrants in the United States in the earnings regression. Specifically, we estimate two probit models predicting emigration to the United States to construct inverse Mills ratios that we include in the earnings regressions based on the sample of Mexican migrants in the United States. For the basic returns earnings regression, we include age and education categories as well as marital status as covariates. For the occupational returns earnings regression, we use cognitive and manual skill quartile categories as covariates. In both models, we include number of children in the household (defined as persons aged below 18 years) in the first stage probit model, but exclude the variable in the second stage model. Results are robust in this approach (see Table H1).

Second, as discussed in Section III.C, we do not expect that Mexican migrants are necessarily aware of the selection bias, but rather form their earnings expectations based on observed differential returns to skills of previous Mexican migrants in the United States (Kaestner and Malamud, 2014). However, our results also hold when we use other comparison groups for calculating differential returns, such as all Mexican migrants, Spanish-speaking migrants from Central and South America (excluding Mexico), and U.S.-born individuals with Mexican ethnicity (see Columns 1–6 of Table H2). They even hold when Mexican migrants would assess their potential returns based on labor-market returns for U.S. natives (Columns 7 and 8 of Table H2). And third, we are mostly interested in the *relative* contribution of basic vs. occupational returns in explaining the negative selection of migrants with respect to earnings, so any selection bias that is common for both return measures does not affect our conclusions.

Furthermore, results are robust to using ENET data (see Table H3). In ENET, adjusting for occupational returns alone is sufficient to explain selection of migrants with respect to earnings (Column 3). This suggests that our occupational return measures, which are based on the 2000 Mexican Census and the 2000 U.S. Census, are somewhat more appropriate for proxying the expected returns of potential Mexican migrants in ENET (conducted from 2000 to 2004) than in ENOE (conducted from 2005 onward).[23]

[23]Unfortunately, earnings in the MMP data are not continuously reported but refer to specific points in the career (e.g., earnings at first/last U.S. trip). This precludes an investigation of earnings selection with the MMP data. The

Finally, results are very similar when we use average earnings over all pre-migration quarters instead of current earnings to assess selection on earnings (see Table H4). Results in this specification rely on a substantially larger sample size as the baseline model because individuals with missing current earnings can also be included.

Table H1: Selection on Earnings and Differential Returns: Selected-Corrected U.S. Return Estimates Using Heckman's (1979) Two-Step Estimator

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.335***	–0.220***	–0.130***	–0.102***	–0.114***
	(0.026)	(0.031)	(0.029)	(0.031)	(0.032)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.572***		0.189***	0.186***
		(0.061)		(0.064)	(0.064)
Δ occupational returns$^{US,2000}_{MEX,2000}$			1.656***	1.575***	1.577***
			(0.105)	(0.111)	(0.111)
Travel distance to U.S. border					–0.008***
					(0.003)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	–0.044	–0.009	0.028	0.035	0.018
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
3rd quintile	–0.284***	–0.228***	–0.154**	–0.143**	–0.165**
	(0.068)	(0.068)	(0.069)	(0.069)	(0.069)
4th quintile	–0.491***	–0.392***	–0.269***	–0.250***	–0.273***
	(0.064)	(0.065)	(0.065)	(0.066)	(0.067)
5th quintile	–0.715***	–0.488***	–0.315***	–0.267***	–0.288***
	(0.059)	(0.067)	(0.064)	(0.069)	(0.069)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.539***		0.156**	0.157**
		(0.061)		(0.064)	(0.064)
Δ occupational returns$^{US,2000}_{MEX,2000}$			1.602***	1.534***	1.540***
			(0.105)	(0.111)	(0.111)
Travel distance to U.S. border					–0.009***
					(0.003)

Notes: Table shows specifications analogous to those in Table 7 using selected-corrected estimates of returns to skills in the United States. Earnings regressions contain a selection correction term (inverse Mills ratio) that is constructed from the parameters of a probit regression of migration indicator on age categories, education categories, and marital status for basic returns and on occupational skill categories for occupational returns. Both probit models include the number of children (persons below 18 years) in the household as the excluded variable in the earnings regression. See Table 7 for sample restrictions and further variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,950,951$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

MxFLS data report occupations only in very broad categories, preventing a meaningful analysis of differential returns to occupational skills.

Table H2: Selection on Earnings and Differential Returns: Using Different Comparison Groups in the United States

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Mexican migrants		Spanish-speaking migrants from Central/South America		U.S.-born with Mexican ethnicity		U.S. natives	
Panel A: Mean selection on earnings								
Dependent variable: migration propensity to the U.S.								
Log hourly earnings	–0.224***	–0.083***	–0.221***	–0.102***	–0.265***	–0.136***	–0.314***	–0.187***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)	(0.031)	(0.030)	(0.030)
Δ basic returns$^{US,2000}_{MEX,2000}$	0.523***	0.048	0.634***	0.271***	0.438***	0.034	0.153**	–0.115
	(0.058)	(0.062)	(0.069)	(0.072)	(0.073)	(0.075)	(0.076)	(0.077)
Δ occupational returns$^{US,2000}_{MEX,2000}$		1.577***		1.364***		1.338***		1.358***
		(0.102)		(0.105)		(0.092)		(0.100)
Panel B: Selection along the earnings distribution								
Dependent variable: migration propensity to the U.S.								
2nd quintile	–0.012	0.041	–0.008	0.045	–0.018	0.028	–0.034	0.021
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.071)
3rd quintile	–0.233***	–0.131*	–0.228***	–0.129*	–0.248***	–0.156**	–0.271***	–0.169**
	(0.068)	(0.068)	(0.068)	(0.069)	(0.068)	(0.069)	(0.068)	(0.069)
4th quintile	–0.400***	–0.229***	–0.393***	–0.239***	–0.432***	–0.277***	–0.473***	–0.311***
	(0.065)	(0.066)	(0.065)	(0.066)	(0.066)	(0.066)	(0.065)	(0.066)
5th quintile	–0.494***	–0.234***	–0.489***	–0.271***	–0.578***	–0.339***	–0.672***	–0.440***
	(0.067)	(0.068)	(0.067)	(0.069)	(0.066)	(0.067)	(0.065)	(0.067)
Δ basic returns$^{US,2000}_{MEX,2000}$	0.497***	0.020	0.602***	0.233***	0.417***	0.005	0.151**	–0.134*
	(0.058)	(0.063)	(0.069)	(0.072)	(0.072)	(0.075)	(0.075)	(0.077)
Δ occupational returns$^{US,2000}_{MEX,2000}$		1.539***		1.327***		1.308***		1.331***
		(0.101)		(0.105)		(0.091)		(0.100)

Notes: Table shows specifications analogous to those in Columns 2 and 4 of Table 7 with returns to skills in the United States calculated based on different population groups. In Columns 1 and 2, U.S. returns are constructed for all Mexican migrants in the United States. In Columns 3 and 4, U.S. returns are constructed for Spanish speaking migrants from Central and South America (excluding Mexico). In Columns 5 and 6, U.S. returns are constructed for U.S. born natives with Mexican ethnicity, and in Columns 7 and 8, U.S. returns are constructed for U.S. natives. See Table 7 for sample restrictions and further variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,950,951$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

Table H3: Selection on Earnings and Differential Returns: Results from ENET

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.268***	–0.125***	–0.016	0.021	–0.011
	(0.020)	(0.026)	(0.026)	(0.028)	(0.029)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.724***		0.287***	0.270***
		(0.052)		(0.052)	(0.053)
Δ occupational returns$^{US,2000}_{MEX,2000}$			1.607***	1.477***	1.478***
			(0.091)	(0.095)	(0.095)
Travel distance to US border					–0.019***
					(0.002)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	0.037	0.093	0.206***	0.213***	0.168***
	(0.061)	(0.062)	(0.063)	(0.063)	(0.064)
3rd quintile	–0.216***	–0.125**	0.032	0.045	–0.022
	(0.058)	(0.060)	(0.061)	(0.061)	(0.063)
4th quintile	–0.474***	–0.317***	–0.113*	–0.088	–0.162***
	(0.054)	(0.057)	(0.059)	(0.060)	(0.062)
5th quintile	–0.766***	–0.415***	–0.182***	–0.114*	–0.189***
	(0.049)	(0.060)	(0.059)	(0.064)	(0.065)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.634***		0.181***	0.171***
		(0.048)		(0.052)	(0.052)
Δ occupational returns$^{US,2000}_{MEX,2000}$			1.495***	1.413***	1.419***
			(0.085)	(0.092)	(0.092)
Travel distance to US border					–0.021***
					(0.003)

Notes: Table shows specifications analogous to those in Table 7 using ENET data. See Table 7 for sample restrictions and variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,564,772$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENET, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

Table H4: Selection on Earnings and Differential Returns:
Using Average Earnings over the Pre-Migration History

	(1)	(2)	(3)	(4)	(5)
Panel A: Mean selection on earnings					
Dependent variable: migration propensity to the U.S.					
Log hourly earnings	–0.340***	–0.146***	–0.031	0.016	–0.004
	(0.025)	(0.030)	(0.029)	(0.031)	(0.032)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.751***		0.270***	0.262***
		(0.053)		(0.056)	(0.056)
Δ occupational returns$^{US,2000}_{MEX,2000}$			1.691***	1.566***	1.570***
			(0.086)	(0.091)	(0.091)
Travel distance to US border					–0.012***
					(0.003)
Panel B: Selection along the earnings distribution					
Dependent variable: migration propensity to the U.S.					
2nd quintile	–0.044	0.004	0.069	0.077	0.052
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
3rd quintile	–0.189***	–0.105*	0.002	0.016	–0.016
	(0.063)	(0.063)	(0.063)	(0.063)	(0.064)
4th quintile	–0.458***	–0.300***	–0.139**	–0.110*	–0.145**
	(0.059)	(0.060)	(0.060)	(0.061)	(0.061)
5th quintile	–0.705***	–0.330***	–0.124**	–0.042	–0.077
	(0.054)	(0.061)	(0.058)	(0.063)	(0.063)
Δ basic returns$^{US,2000}_{MEX,2000}$		0.710***		0.225***	0.223***
		(0.052)		(0.055)	(0.055)
Δ occupational returns$^{US,2000}_{MEX,2000}$			1.628***	1.524***	1.532***
			(0.084)	(0.091)	(0.090)
Travel distance to US border					–0.013***
					(0.003)

Notes: Table shows specifications analogous to those in Table 7 using average earnings, constructed as simple average of log hourly earnings in pre-migration quarters. See Table 7 for sample restrictions and variable definitions. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 2,416,021$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

I Migration Status and Immigration Policies

In this appendix, we discuss the role of U.S. immigration policies, the duration of migration, and legal migration status for our results. For this analysis, we mainly use the MMP data, which contain rich background information on migrants (including legal status) and provide time coverage from the 1950s to present. We begin by investigating whether the prevailing pattern of selection reflects differences between the labor markets in Mexican and the United States, as we argue, or is rather induced by the U.S. immigration policy. We show that, despite major changes in U.S. border policies influencing the migration behavior of Mexicans (e.g., termination of the Bracero program in 1964 or implementation of the Immigration Reform and Control Act (IRCA) in 1986), the pattern of selection on occupational skills remained remarkably stable over time.

Second, temporary migration episodes of Mexicans in the United States are frequent. However, this is unlikely to affect our results much. For instance, when dropping migrants with a temporary U.S. contract (i.e., Bracero or H-2A visa in the MMP) or a temporary U.S. work permit (about 16% of the migrant sample in the MMP), results are very similar as in the full sample. In ENOE, our results are also robust to dropping temporary migrants or agricultural workers (who are most likely to migrate for seasonal and short-term work, e.g., by making use of the H-2A and H-2B visa programs). To further address seasonal migration, we show that selection on occupational skills does not follow any seasonal pattern. Regarding return migration, we find that return migrants have higher cognitive skills and lower manual skills than other migrants (i.e., are more similar to Mexican residents). This is in line with our theoretical predictions because the skill set of return migrants should be rewarded more in Mexico than in the United States; otherwise, they would have no benefit-driven incentive to return home. We conclude that results in our baseline sample (which contains both future return migrants and permanent migrants) likely underestimate the true selection pattern for permanent migrants; that is, Mexican migrants who permanently stay in the United States are likely even more positively selected on manual skills and more negatively selected on cognitive skills than suggested by our baseline results.

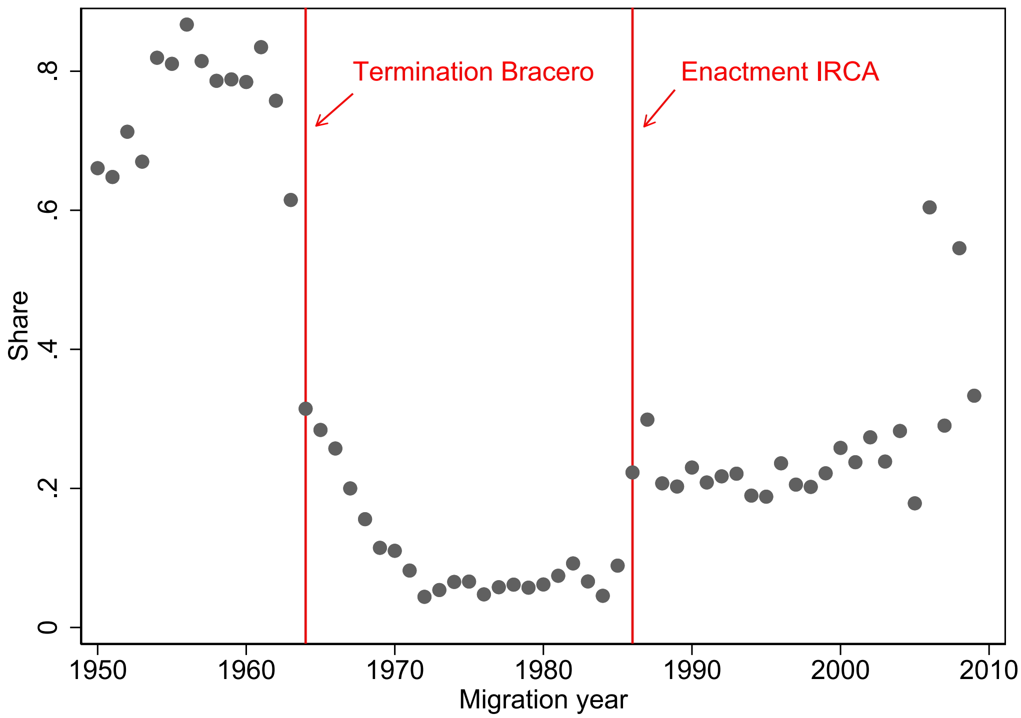
Third, we investigate whether the selection pattern differs between migrants with a legal migration status ("documented migrants") and those who are unauthorized, did not know their migration status, or refused to report their status ("undocumented migrants"). We find that there is positive selection on manual skills and negative selection on cognitive skills for both migrant groups, with a very similar strength of selection. However, one may argue that working illegally in occupations in which the individual is more visible for customers (and thus also for immigration and law enforcement officers) yields a higher risk of deportation than working in occupations with lower visibility. In turn, the higher deportation risk may lead to lower expected migration benefits when working in high-visibility occupations. Using the required communication skills in an occupation (see Appendix C.C) to proxy a worker's degree of visibility, we show that the selection pattern is similar in occupations with a high (i.e., above-median) visibility and in those with a low (i.e., below-median) visibility. Thus, legal status of migrants and risk of deportation are unlikely to be a major driver of our results.

A Immigration Policies

We first turn to the question whether the observed pattern of selection may be driven by the U.S. immigration policy, which induced changes in the composition of Mexican migrants with respect to their legal status. U.S. immigration policy governing Mexican migration to the United States underwent substantial changes in the past (for overviews, see Durand and Massey, 2004; Massey et al., 2015). Figure I1 shows how the share of documented migrants in all migrants from Mexico to the United States responded to these policy reforms. The figure is based on information from the MMP data on migration episodes and the legal status in which trips were made. Until 1964, migration from Mexico to the U.S. was largely determined by the Bracero Program,[24] a binational temporary labor program that annually sponsored the entry of Mexicans for short-term work in the United States. In 1964, the U.S. Congress terminated the Bracero program, leading to a massive reduction of documented migration from Mexico to the U.S. Given the continuing labor demand and well-developed migrant networks, the inflow of Mexican migrants did not cease, but simply continued under undocumented auspices. Accordingly, the share of documented migrants decreases considerably after 1964. This changed again in 1986 when Congress passed the Immigration Reform and Control Act (IRCA) that, among other things, launched a massive increase in border enforcement. As a result, documented migration has risen relative to undocumented migration after the enactment of IRCA and the progressive militarization of the Mexico-U.S. border that came with it. More recently, the Great Recession led to a substantial decrease in the absolute number of undocumented Mexican migrants, resulting in a further increase of the share of documented migrants.

[24]The Spanish term *bracero* means "manual laborer" or "one who works using his arms." The program was initiated in 1942, when the United States signed the Mexican Farm Labor Agreement with Mexico.

Figure I1: Share of Documented Mexican Migrants Over Time



Notes: Graph shows share of documented Mexican emigrants to the United States by migration year. Vertical red lines indicate major changes in U.S. immigration policies. *Data source:* MMP.

Despite these changes in U.S. border policies and their apparent influence on migration behavior of Mexicans, the pattern of selection on occupational skills remained remarkably stable over time. Table I1 presents our baseline model for three periods whose respective end dates are defined by marked changes in U.S. immigration policies; that is, the termination of the Bracero Program in 1964 and the launch of the IRCA in 1986. Across all three periods, we observe negative selection on cognitive skills and positive selection on manual skills. While the qualitative selection pattern is stable over time, the strength of selection does change. In particular, the selection pattern is most pronounced under the auspices of the Bracero Program (i.e., 1950–1964), reflecting that this program was targeted at laborers from Mexico (i.e., workers with high manual and low cognitive skills).

The evidence presented in Table I1 adds to our analysis of the long-run dynamics of selection on occupational skills, which shows that negative selection on cognitive skills and positive selection on manual skills prevails over the entire sample period, that is, from 1950 to 2013 (see Figure G1). We therefore consider it highly unlikely that changes in U.S. immigration policies over time or the current U.S. immigration policy are main drivers of the selection pattern we observe.

Table I1: Emigrant Selection on Occupational Skills Within Periods of Homogeneous U.S. Immigration Policies Toward Mexico

	(1)	(2)	(3)
	1950–1964	1965–1986	1987–2011
Dependent variable: migration propensity to the U.S.			
Cognitive skills	–0.145***	–0.116***	–0.127***
	(0.030)	(0.021)	(0.022)
Manual skills	0.159***	0.099***	0.061**
	(0.037)	(0.031)	(0.029)
Cognitive skills × manual skills	–0.059***	–0.032***	–0.019**
	(0.013)	(0.007)	(0.008)
Years of schooling	0.013	–0.016*	–0.026***
	(0.013)	(0.009)	(0.009)
Age	–0.011***	–0.042***	–0.051***
	(0.004)	(0.003)	(0.003)
Observations	63,020	222,849	185,254
Average migration rate (in %)	3.14	2.40	2.14

Notes: Sample includes Mexican males aged 16 to 65. In each column, only migration moves in the time period indicated in the column header are included. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by sample-specific annual migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations prior to migration. Skill measures are demeaned and scaled by 10. All regressions contain year fixed effects. Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the individual level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* MMP, Mexican CONOCER, and U.S. O*NET.

B Temporary vs. Permanent Migration

Much of the Mexican migration is temporary in nature, and many Mexicans migrate to the United States multiple times. Moreover, most visa categories for short-term migration (e.g., H-2A and H-2B) are predominately for workers in low-cognitive and high-manual occupations. However, neither temporary migration nor return migration is likely to affect our results much. First, dropping migrants with a temporary U.S. contract (i.e., Bracero or H-2A visa) or a temporary U.S. work permit (about 16% of the migrant sample in the MMP) leads to very similar results as in the full sample (Column 1 of Table I2). The same is true when we drop return migrants (Column 2).

Second, Table I3 shows that the selection pattern remains similar when we drop (likely) temporary migrants in ENOE. Since ENOE does not provide unique identifiers for temporary migrants, we categorize an international migrant as temporary when a new household member appears within the observed five quarters who has the same gender and age (or being older by one year) as the international migrant. The approach yields that among the 8,701 international migrants in the ENOE, 1,072 (12%) are (likely) temporary migrants.

Third, again using ENOE data, we can show that results are robust to dropping agricultural workers (Figure I2), who are most likely to migrate for seasonal and temporary work (e.g., by making use of the H-2A visa program).[25] Moreover, if our results were due to the presence of temporary and seasonal migrants, the degree of negative selection on cognitive skills and positive selection on manual skills should be more pronounced in the periods of the year when seasonal migration takes place. However, we do not find any seasonal pattern when investigating selection on occupational skills by quarter (Figure I3).

Table I2: Emigrant Selection on Occupational Skills: Permanent Migrants (MMP)

	(1)	(2)
	No temporary contracts or work permits	No return migrants
Dependent variable: migration propensity to the U.S.		
Cognitive skills	–0.124***	–0.124***
	(0.015)	(0.017)
Manual skills	0.072***	0.051**
	(0.022)	(0.025)
Cognitive skills × manual skills	–0.026***	–0.031***
	(0.006)	(0.007)
Years of schooling	–0.016**	–0.012*
	(0.007)	(0.007)
Age	–0.045***	–0.067***
	(0.002)	(0.002)
Observations	469,419	464,277
Average migration rate (in %)	2.05	1.24

Notes: Table presents baseline results for permanent migrants. In Column 1, we drop migrants with a temporary U.S. contract (Bracero program or H2A visa) or work permit (16.28% of migrant sample). In Column 2, we drop all migrant observations after the first move to the United States, that is, estimation is without return migrants (52.12% of migrant sample). Sample includes Mexican males aged 16 to 65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by sample-specific annual migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations prior to migration. Skill measures are demeaned and scaled by 10 All regressions contain year fixed effects. Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the individual level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* MMP, Mexican CONOCER, and U.S. O*NET.

[25] Agriculture is also the largest occupation in Mexico, constituting 12.6% of the entire sample in ENOE.

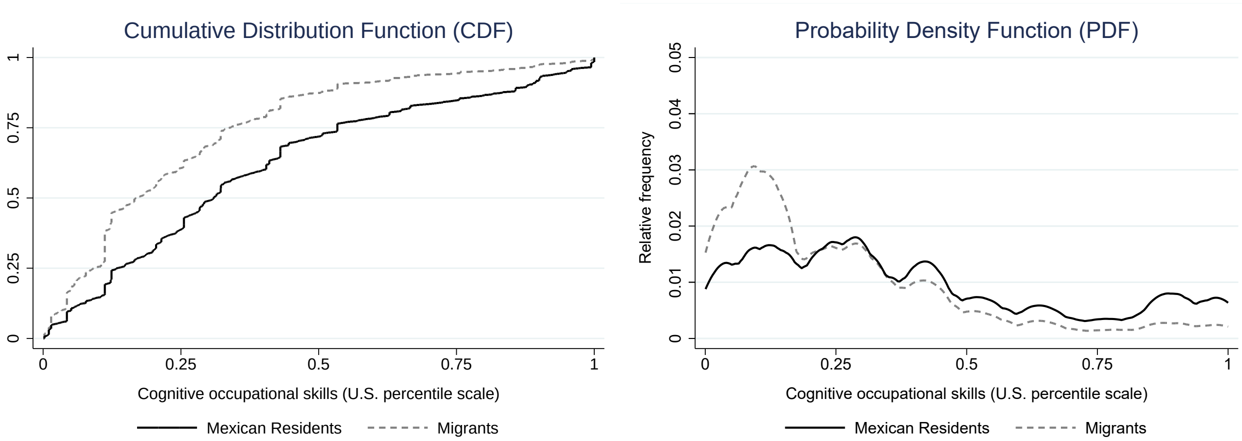
Table I3: Emigrant Selection on Occupational Skills: Permanent Migrants (ENOE)

	(1)	(2)	(3)	(4)
	National labor market		Narrow labor markets	
	Baseline	No temporary migrants	Baseline	No temporary migrants
Cognitive skills	–0.164***	–0.166***	–0.088***	–0.107***
	(0.009)	(0.009)	(0.020)	(0.021)
Manual skills	0.182***	0.182***	0.084**	0.092**
	(0.014)	(0.015)	(0.036)	(0.036)
Cognitive skills × manual skills	–0.079***	–0.081***	–0.026**	–0.031***
	(0.005)	(0.005)	(0.011)	(0.011)
Years of schooling	0.010*	0.012**	0.031***	0.032***
	(0.005)	(0.005)	(0.007)	(0.007)
Age	–0.032***	–0.033***	–0.034***	–0.036***
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	2,959,528	2,958,456	2,959,528	2,958,456
Average migration rate (in %)	1.35	1.62	1.35	1.62

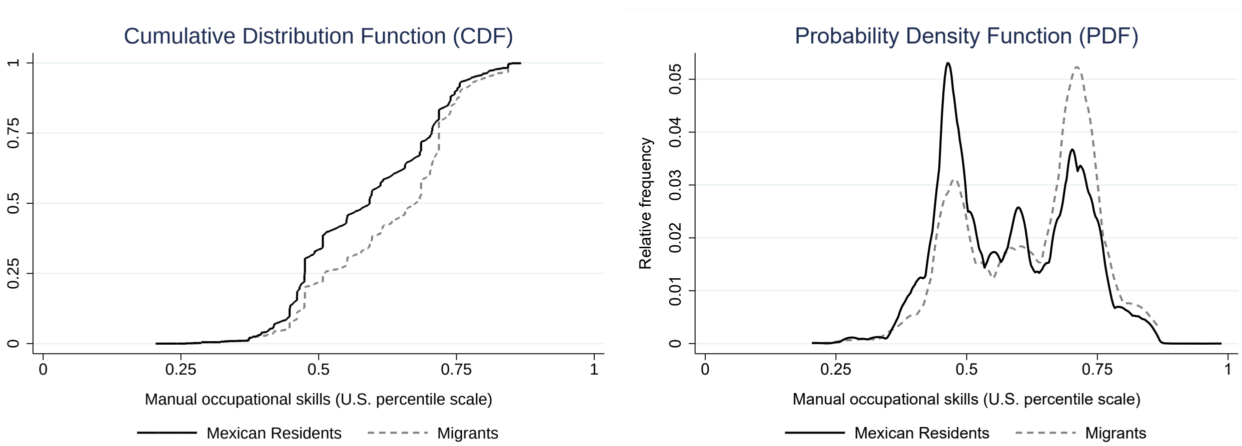
Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Skill measures are demeaned and scaled by 10. Column 1 shows baseline results from Column 3 of Table 2. Column 2 drops (likely) temporary migrants, i.e. those international migrants who return within the observed five quarters to the same household. Columns 3 and 4 repeat the same regressions within narrow labor markets. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Figure I2: Emigrant Selection on Occupational Skills: Omitting Agricultural Workers

(a) Cognitive Occupational Skills

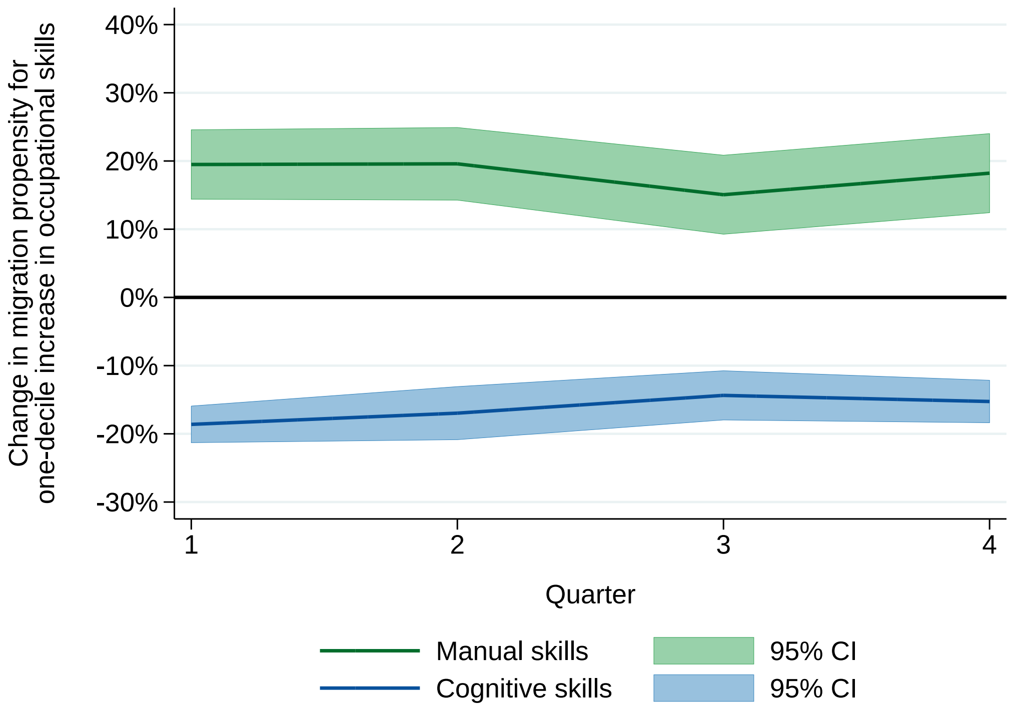


(b) Manual Occupational Skills



Notes: Figures show cumulative distribution functions (left panels) and probability density functions (right panels) of cognitive occupational skills (Figure I2(a)) and manual occupational skills (Figure I2(b)) by migration status. Sample consists of male Mexicans aged 16–65, no agricultural workers. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Kolmogorov-Smirnov tests on stochastic dominance indicate that differences between cumulative distribution functions are significant at the 1% level. $N = 6,665$ Mexican migrants in the United States and $N = 2,686,836$ Mexican residents. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Figure I3: Emigrant Selection by Quarter



Notes: Graph shows selection on cognitive and manual skills (based on the specification in Column 3 of Table 2) when data are grouped by quarter. *Data sources:* CONOCER and ENOE.

Fourth, the ENOE also allows to identify return migrants. We classify a person as return migrant when that person is a new household member during the observation period. Out of 2,955,699 person-quarter observations in ENOE, we identify a total of 4,872 persons (with valid occupational and educational information) who return to Mexico in a given quarter. Obviously, this classification procedure misses returnees who returned at some point before the survey. In other words, ENOE does not allow us to capture the stock of return migrants, but only its flow (as is also the case with international migrants to the United States). In the baseline analysis, return migrants are not included because in ENOE they are not coded as residents in the quarter when they return to Mexico. Not surprisingly given their negligible number, adding return migrants to the sample of Mexican residents does not change our results at all (i.e., all coefficients remain exactly the same as in our baseline analysis).

In further analysis, we compare the occupational skill distribution of return migrants to the occupational skills of Mexican residents and the migrant sample used in the main analysis (i.e., without return migrants); following the notation in the remainder of the paper, we refer to the latter simply as *migrants*. Figure I4 shows the respective CDFs. We observe that the cognitive skill distribution of return migrants is between the distributions for residents and migrants. This means that return migrants have lower cognitive skills than Mexican residents but higher cognitive skills than migrants. The reverse is true for manual skills. Table I4 corroborates this picture by reporting average skills as well as the 25th, 50th, and 75th skill percentiles for residents, migrants, and return migrants.

The finding that return migrants have higher cognitive skills and lower manual skills than other migrants (i.e., are more similar to Mexican residents) is in line with our theoretical predictions because the skill set of return migrants should be rewarded more in Mexico than in the United States; otherwise, they would have no benefit-driven incentive to return home. We conclude that results in our baseline sample (which contains both future return migrants and permanent migrants) likely underestimate the true selection pattern for permanent migrants; that is, Mexican migrants who permanently stay in the United States are likely even more strongly positively selected on manual skills and more strongly negatively selected on cognitive skills than suggested by our baseline results.

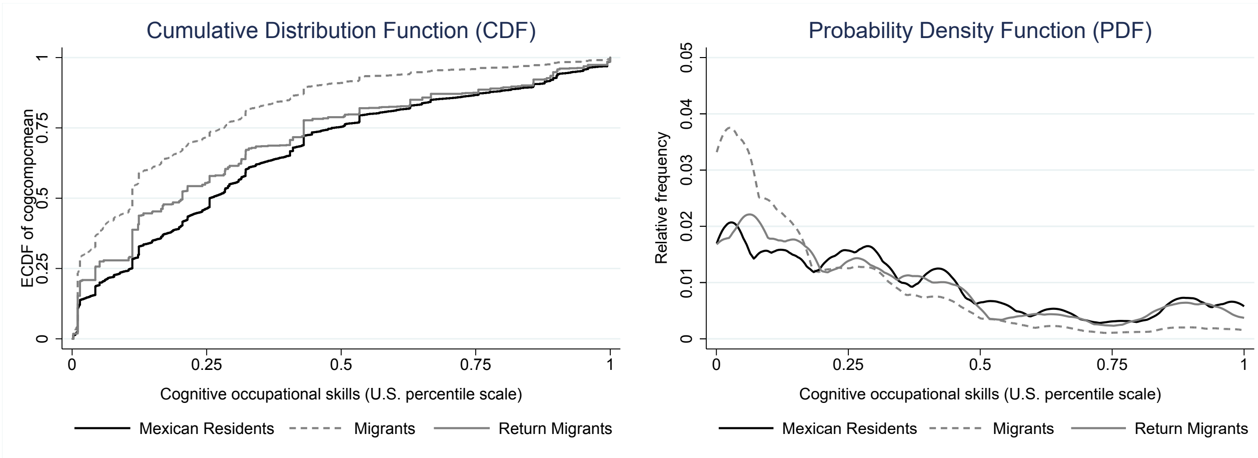
Table I4: Comparison of Occupational Skills by Migrant Status

	(1)	(2)	(3)	(4)
Group	Average	P25	P50	P75
Cognitive skills				
Mexican residents	0.332	0.109	0.255	0.482
International migrants	0.183	0.012	0.111	0.281
Return migrants	0.292	0.043	0.204	0.43
Manual skills				
Mexican residents	0.609	0.475	0.612	0.718
International migrants	0.669	0.589	0.705	0.770
Return migrants	0.628	0.475	0.683	0.739

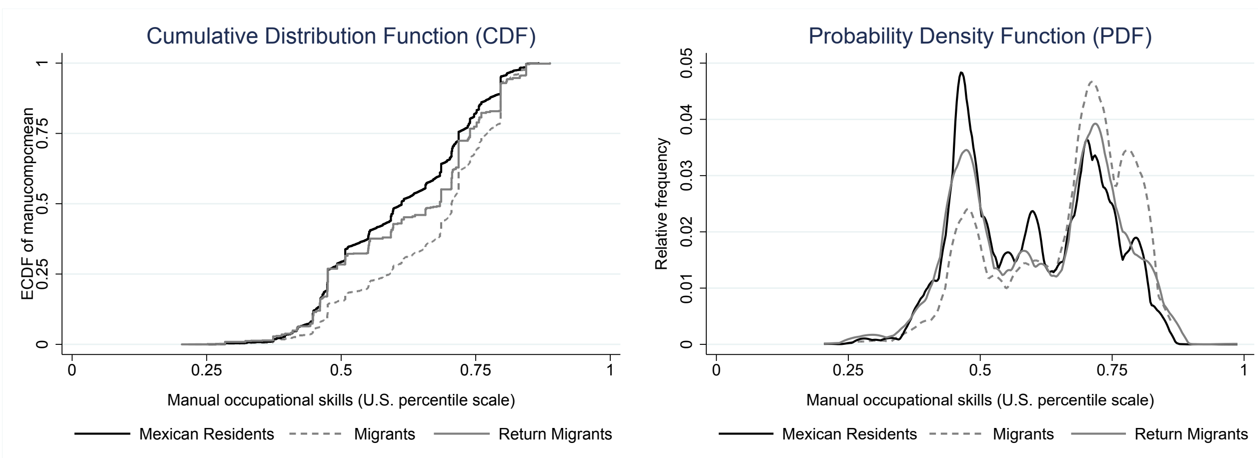
Notes: Table shows average, 25th percentile, 50th percentile, and 75th percentile of the occupational skills distribution by migration status. Sample consists of male Mexicans aged 16-65. Cognitive and manual skills incorporate full observed pre-migration worker history: they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. $N = 8,701$ Mexican migrants in the United States, $N = 4,872$ return migrants from the United States, and $N = 2,950,827$ Mexican residents. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Figure I4: Emigrant Selection on Occupational Skills: Including Return Migrants

(a) Cognitive Occupational Skills



(b) Manual Occupational Skills



Notes: Figures show cumulative distribution functions (left panels) and probability density functions (right panels) of cognitive skills (Figure I4(a)) and manual skills (Figure I4(b)) by migration status. Sample consists of male Mexicans aged 16-65. Cognitive and manual skills incorporate full observed pre-migration worker history: they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. $N = 8,701$ Mexican migrants in the United States, $N = 4,872$ return migrants from the United States, and $N = 2,950,827$ Mexican residents. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

C Documented vs. Undocumented Migration

Legal Status and Selection on Occupational Skills

First, we checked in the MMP data how documented and undocumented migrants differ in terms of occupational skills. In the data, 27% of migrants have a legal migration status (“documented migrants”). The remaining sample consists of unauthorized migrants and of those who did not know or refused to report their migration status (“undocumented migrants”). We find that documented migrants have somewhat *lower cognitive skills* (0.13 vs. 0.14) and *higher manual skills* (0.73 vs. 0.71) than their undocumented counterparts. Moreover, we also checked how the share of migrants who worked in high-cognitive or high-manual jobs before migration differs between documented and undocumented migrants. Corroborating the previous results, we find that the share of documented migrants with above-median cognitive skills (21.4%) is significantly lower than the respective share for undocumented migrants (32.8%). In contrast, the share of documented migrants with above-median manual skills (78.7%) is significantly higher than the respective share for undocumented migrants (67.2%). The fact that undocumented migrants have higher cognitive and lower manual skills than their documented peers refutes the claim that the selection pattern could be induced by the reluctance of undocumented migrants to work in high-cognitive jobs.

Second, we checked to what extent the pattern of selection on occupational skills differs by legal migration status. We find that there is positive selection on manual skills and negative selection on cognitive skills for both migrant groups, with a very similar strength of selection (Table I5).

Third, we checked whether our results are driven by differences across occupations in the degree of visibility, possibly affecting the deportation risk. If the transferability of cognitive skills takes more time than the transferability of manual skills, the risk of short-term migration could induce differential expected returns of manual vis-à-vis cognitive skills (even if the true returns to both skills would be the same). Since none of our datasets includes a direct measure of visibility, we constructed an occupational-level proxy for visibility using our measure of communication skills (see Section IV.B for details). This measure supposedly captures an occupation's degree of customer interaction. We conjecture that occupations with a higher degree of customer interaction are likely those which are more visible in the United States, also to immigration and law enforcement officers, increasing the risk of deportation for undocumented migrants. To investigate whether differences in the visibility across occupations can explain our results, we performed a subsample analysis in which we differentiate between (four-digit level) occupations with high (i.e., above-median) or low (i.e., below-median) visibility.[26] Table I6 shows the results when we run our baseline specification separately on both samples. At the national level (Columns 2 and 3), we observe negative selection on cognitive skills and positive selection on manual skills in high-visibility occupations and in low-visibility occupations. In fact, the strength of selection is very similar in both samples. This also holds within narrow labor markets (Columns 5 and 6), although the coefficient on manual skills in the high-visibility sample, albeit positive and sizable, is not significant due to the low precision of the estimate. Given this evidence, we consider it unlikely that differences in visibility and thus in the risk of return/deportation explain the observed selection pattern.

[26] Since median visibility is defined at the occupational level, the number of person-year observations differs across both samples.

Table I5: Emigrant Selection on Occupational Skills by Legal Migration Status

	(1)	(2)
	Documented migrants	Undocumented migrants
Dependent variable: migration propensity to the U.S.		
Cognitive skills	–0.140***	–0.117***
	(0.042)	(0.016)
Manual skills	0.085*	0.085***
	(0.049)	(0.022)
Cognitive skills × manual skills	–0.017	–0.028***
	(0.017)	(0.006)
Years of schooling	0.068***	–0.032***
	(0.017)	(0.007)
Age	–0.008*	–0.051***
	(0.004)	(0.002)
Observations	463,435	468,347
Average migration rate (in %)	0.64	1.79

Notes: Table presents baseline results by legal migration status. In Column 1, sample of Mexican migrants includes only persons who migrate to the United States with official U.S. documentation (i.e., legal residence permit, contracts (Bracero program or H2A visa), and temporary work permits); 26.53% of migrant sample. In Column 2, sample of Mexican migrants includes only migrants without official U.S. documentation (including illegal migrants); 73.47% of migrant sample. Sample includes Mexican males aged 16 to 65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by sample-specific annual migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations prior to migration. Skill measures are demeaned and scaled by 10 All regressions contain year fixed effects. Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the individual level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* MMP, Mexican CONOCER, and U.S. O*NET.

Table I6: Emigrant Selection on Occupational Skills by Degree of Occupational Visibility

	(1)	(2)	(3)	(4)	(5)	(6)
	National labor market			Narrow labor markets		
	Baseline	Visibility		Baseline	Visibility	
		Low	High		Low	High
Dependent variable: migration propensity to the U.S.						
Cognitive skills	–0.127***	–0.150***	–0.158***	–0.084***	–0.067***	–0.071*
	(0.008)	(0.011)	(0.018)	(0.019)	(0.025)	(0.038)
Manual skills	0.210***	0.199***	0.189***	0.097**	0.128***	0.084
	(0.015)	(0.015)	(0.040)	(0.039)	(0.040)	(0.108)
Years of schooling	0.009*	0.006	0.001	0.031***	0.032***	0.014
	(0.005)	(0.006)	(0.011)	(0.007)	(0.007)	(0.015)
Age	–0.031***	–0.032***	–0.031***	–0.034***	–0.033***	–0.036***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)
Observations	2,959,528	1,875,952	1,083,576	2,959,528	1,875,952	1,083,576
Average migration rate (in %)	1.35	1.62	0.83	1.35	1.62	0.83

Notes: Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by quarterly migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four pre-migration quarters. Skill measures are demeaned and scaled by 10. Column 1 shows baseline results from Column 3 of Table 2 without the cognitive-manual-skill interaction. Columns 2 and 3 split occupations at the four-digit level according to required communication skills (see Appendix C.C). *Low* (*High*) refers to occupations, which require below (above) median communication skills (U.S. communication skill distribution). Columns 4 to 6 repeat the same regressions within narrow labor markets. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Legal Status and Returns to Skills

A related concern is that migrants who consider moving to the United States illegally may expect lower returns to cognitive skills than their documented counterparts. Thus, one may question whether our results in Section V on differential returns to occupational skills between Mexico and the United States equally apply to documented and undocumented migrants. We apply the approach by Borjas (2017) to distinguish between “likely authorized” and “likely unauthorized” migrants in the U.S. Census data. Following Passel and Cohn (2014), who use a residual-approach to estimate the number of undocumented migrants based on Census data, Borjas adopts the same methodology and categorizes a migrant as “likely authorized” when at least of the following conditions applies:

- the person has arrived in the United States before 1980;
- the person is a U.S. citizen;
- the person receives social security benefits, supplemental security income (SSI), medicaid, medicare, or military insurance;
- the person is a veteran or currently in the armed forces;

- the person works in the government sector;
- the person resides in public housing or receives rental subsidies (or is a spouse of someone who resides in public housing or receives rental subsidies);
- the person is born in Cuba (as practically all Cuban immigrants were granted refugee status before 2017);
- the person's occupation requires some form of licensing (such as physicians, registered nurses, air traffic controllers, and lawyers);
- the person's spouse is a legal immigrant or citizen.[27]

We proceed by repeating the Mincer earnings regressions from Appendix F to show that the authorization status does not play a major role for the estimated returns to occupational skills. Panel A of Table I7 starts with splitting the sample of recent Mexican migrants by authorization status. The coefficients for likely unauthorized migrants are generally smaller than those for likely authorized migrants. However, the coefficients on the returns to manual skills remain large in both samples, while the coefficients on the returns to cognitive skills are below the respective coefficient for Mexican residents in the Mexican Census (Columns 3 and 6 in Panel A of Table I7 vs. Column 3 of Table F1).[28] Thus, for both likely authorized and likely unauthorized Mexican migrants in the United States, we find that returns to manual skills are higher in the United States and that returns to cognitive skills are higher in Mexico. A similar picture emerges when we pool recent and non-recent Mexican migrants in Panel B of Table I7.

In Table I8, we show the relationship with the propensity to migrate of differential returns to basic and occupational skills, where the differential returns are estimated separately for likely authorized migrants (Column 2) and likely unauthorized migrants (Column 3). We find very similar coefficients on both returns differentials. The differential-returns estimates are also very similar to those in the baseline (Column 1). The similar pattern is consistent with the above result from the MMP analysis that the selection on occupational skills is very similar for documented and undocumented migrants.

[27]As Borjas applies his methodology to CPS data, we cannot implement each of these restrictions. In fact, the U.S. Census 2000 does not provide indicators for receiving medicaid, medicare, or military insurance, and does neither allow identifying persons who reside in public housing or receive rental subsidies. Instead, we additionally classify individuals as likely authorized when they have received some welfare payments.

[28]The latter coefficient is equal to 0.0510 and significant at the 1% level.

Table I7: Returns to Occupational Skills in the United States by Authorization Status

	(1)	(2)	(3)	(4)	(5)	(6)
	Likely authorized migrants			Likely unauthorized migrants		
Panel A: Recent Mexican migrants						
Dependent variable: log hourly earnings						
Manual skills	0.0206***	0.0239***		0.0137***	0.0220***	
	(0.0038)	(0.0041)		(0.0023)	(0.0024)	
Cognitive skills	0.0559***		0.0446***	0.0501***		0.0358***
	(0.0040)		(0.0044)	(0.0026)		(0.0029)
R-squared	0.103	0.110	0.112	0.063	0.072	0.070
	$N = 11,818$; median manual skills = 0.852, median cognitive skills = 0.204.			$N = 45,552$; median manual skills = 0.867, median cognitive skills = 0.133.		
Panel B: All Mexican migrants						
Dependent variable: log hourly earnings						
Manual skills	0.0229***	0.0262***		0.0168***	0.0243***	
	(0.0019)	(0.0021)		(0.0018)	(0.0020)	
Cognitive skills	0.0598***		0.0455***	0.0523***		0.0394***
	(0.0020)		(0.0021)	(0.0021)		(0.0023)
R-squared	0.108	0.116	0.117	0.073	0.081	0.080
	$N = 50,178$; median manual skills = 0.852, median cognitive skills = 0.202.			$N = 65,039$; median manual skills = 0.854, median cognitive skills = 0.133.		
Control variables	x	x	x	x	x	x
Cognitive skill decile fixed effects		x			x	
Manual skill decile fixed effects			x			x

Notes: Panel A shows returns to cognitive and manual occupational skills for recent Mexican migrants who migrated to the United States between 1990 and 2000 in the 2000 U.S. Census by likely authorization status (cf. Panel A in Appendix Table F2). Panel B shows returns to cognitive and manual occupational skills for all Mexican migrants who migrated to the United States between 1990 and 2000 in the 2000 U.S. Census by likely authorization status. All regressions condition on a full set of control variables: education (five categories), age (six categories), marital status, state-of-living fixed effects, and metropolitan area status. Columns (2) and (5) contain decile fixed effects of cognitive skills, and Columns (3) and (6) contain decile fixed effects of manual skills. Decile cutoffs are taken from the occupational skill distribution in the Mexican Census 2000. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* 2000 U.S. Census (5% sample), Mexican CONOCER, and U.S. O*NET.

Table I8: Selection on Earnings and Differential Returns:
Results for Returns by Authorization Status of the Migrants

	(1)	(2)	(3)
	Baseline	Returns by authorization status	
		Authorized	Unauthorized
Dependent variable: migration propensity to the U.S.			
Log hourly earnings	–0.050	–0.055*	–0.044
	(0.032)	(0.030)	(0.031)
Δ basic returns$^{US,2000}_{MEX,2000}$	0.242***	0.297***	0.214***
	(0.061)	(0.060)	(0.056)
Δ occupational returns$^{US,2000}_{MEX,2000}$	1.497***	1.430***	1.476***
	(0.099)	(0.091)	(0.092)
Travel distance to US border	–0.008***	–0.008***	–0.008***
	(0.003)	(0.003)	(0.003)

Notes: The table repeats the regression in Column 5 of Panel A in Table 7 with different return specifications. Column 2 uses the returns from likely authorized migrants and Column 3 uses the returns from likely unauthorized migrants. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. $N = 1,950,951$. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, U.S. O*NET, 2000 Mexican Census (10.6% sample), and 2000 U.S. Census (5% sample).

Legal Status and Skill Transferability

Finally, the legal status of Mexican migrants might also affect the degree to which skills can be transferred from Mexico to the United States. For instance, migrants with a comparative advantage in cognitive skills who are documented might enjoy a higher transferability of their skills than their counterparts who migrate illegally to the United States and are thus forced into worse (i.e., less cognitive-intense) jobs. This would imply that our general result that there is a high degree of skill transferability when Mexicans migrate to the United States (see Section B) might not hold for undocumented migrants.

To see whether this is a valid concern, we checked in the MMP data to what extent documented and undocumented migrants differ in their occupational switching behavior after migration. We observe that documented migrants are much more likely to stay in their previous occupation than their undocumented counterparts. In 56.4% of cases, documented migrants work in the same occupation as in Mexico upon entry in the United States; for undocumented migrants, this share is only 30%.

Conditional on occupational switching, documented migrants tend to switch to jobs that are less cognitive and more manual than the job last held in Mexico; for undocumented migrants, the pattern is exactly opposite. In fact, 62.9% of occupational switches of documented migrants are to a less cognitive-intense job (undocumented migrants: 43.2%), while 59.8% of switches are to a high manual-intense job (undocumented migrants: 39.5%). This indicates that those documented migrants who change occupations (i.e., do not manage or do not want to find a job in "their" occupation) often switch downward in cognitive skills and upward in manual skills. In contrast, undocumented migrants who switch occupations often switch upward in cognitive skills and downward in manual skills.

Finally, on average across all migrants, the mean change in cognitive and manual skills is very small (counting occupational stayers as zero change): for documented (undocumented) migrants, the average absolute distance of an occupational switch is only 2.6 (0.09) percentiles for cognitive and 1.1 (3.2) percentiles for manual. The median distance is zero for cognitive and manual skills for both migrant types. However, conditional on occupational switching, documented migrants tend to switch over larger skill distances than their undocumented peers, especially when considering cognitive skills. On average, documented migrants switch to jobs that are 9.6 percentiles less cognitive-intense and 4.3 percentiles more manual-intense than the previous job. Undocumented migrants who change occupations upon migration to the U.S. switch to occupations with 0.15 percentiles higher cognitive skills and 5.4 percentiles lower manual skills.

Overall, for both documented and undocumented migrants, we find that a considerable share of migrants remains in the same occupation after moving to the United States and that the average distance of occupational moves is rather small. This suggests a high degree of skill transferability when workers migrate–for both documented and undocumented migrants. However, differentiating by migrant status also reveals some interesting differences. For documented migrants, switching occupations often means an occupational downgrade (in particular, in terms of cognitive skills), while the majority of undocumented migrants who switch occupations manages to move to a better (i.e., more cognitive-intense) job.

J Endogenous Skill Formation

This appendix addresses endogenous skill formation. Starting with a general point, endogenous skill formation should be relevant for our results only at the margin. That is, if an individual could choose between a high-manual/low-cognitive occupation and a low-manual/high-cognitive occupation at the same costs, income maximization would always lead to preferring the low-manual/high-cognitive occupation ("you will not become a farmer if you could become a heart surgeon"). In other words, in either country, the returns structure is such that it is always more highly rewarded to take a cognitive-intense job than a manual-intense job. However, for individuals with the same level of cognitive skills, a prospective migrant may decide to invest more in manual skills than the non-migrant because returns to manual skills in the U.S. are larger than in Mexico. This endogeneity issue would only invalidate our results if—without the incentive effect through the relatively high returns to manual skills in the U.S.—migrants would actually have lower manual skills than non-migrants. Given that (i) migrants have substantially higher manual skills than non-migrants and (ii) returns to manual skills (in both Mexico and the U.S.) are considerably lower than returns to cognitive skills in either country, it seems a priori unlikely that this "incentive effect" is strong enough to reverse our results.

The remainder of the appendix provides evidence indicating that endogenous skill formation is not a major issue for our analysis. First, if people switched occupations systematically because they want to move to the United States, we should observe differences in the selection pattern when using information from the first observed quarter compared to using information from, say, the quarter directly before the move. This, however, is not the case. The selection pattern is very similar regardless of which quarter we choose to calculate the occupational skill scores.

Second, among all occupations held by a worker in his career, the first occupation is least likely to be affected by migration decisions later in life. In an instrumental-variable (IV) analysis, we exploit long-run dynamics of occupational choices, using an individual's occupation at labor-market entry as an instrument for his current occupation. Results show that occupational skills early in the career are a good approximation of skills at migration, suggesting that workers try to avoid switching to occupations that involve significant changes in job content. Unless workers plan future migration already very early in their careers, and choose even their first job according to the perceived returns to migration, the IV results alleviate the concern that occupational skill acquisition is endogenous to migration.

Third, we investigate the likelihood of job changes (e.g., towards low-cognitive / high-manual jobs) prior to the first migration episode. We find that the propensity to switch jobs even in the five years before first migrating to the United States is very low, which is also at odds with the idea of job choices being endogenous to migration.

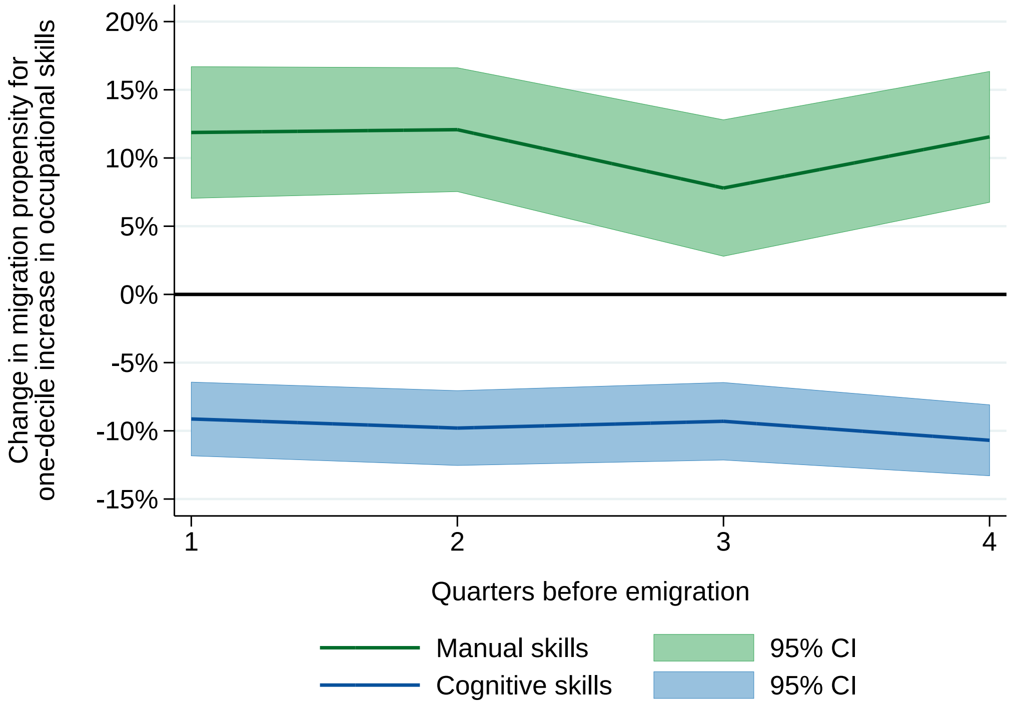
A Using Occupational Information from Different Pre-Migration Quarters

First, instead of using only the last (and potentially endogenous) pre-migration occupation to measure occupational skills, our main results are based on the (unweighted) average of the skill content of current and all observed previous occupations until (potential) migration. Still, since our baseline results are based on the ENOE data, we can observe only up to four quarters prior to migration. Thus, our occupational skill measures are strongly affected by the last (and potentially most endogenous) pre-migration occupation. Figure J1 shows that the selection pattern is always very similar when we use the occupation held four, three, two, or one quarter before migration to measure occupational skills (i.e., when we use only the occupational information from the same quarter for each individual). If people switched occupations systematically because they want to move to the United States, we should observe differences in the selection pattern when using information from, say, the first observed quarter compared to using information from the quarter directly before the move. This, however, is not the case.

This analysis also addresses another potential concern, namely, that those who decide to migrate received a negative labor-market shock right before the migration move (e.g., job displacement), pushing them to low-cognitive, high-manual jobs. The evidence in Figure J1 suggests that imperfect job matches due to skill-specific labor-market shocks are unlikely to affect our results.

There is also reason to suspect that skill mismatch (as a potential driver of migration) systematically varies over the career, as early-career workers are more likely to experience skill mismatch than higher-tenured workers (e.g., Jovanovic, 1979; Hanushek et al., 2015). We therefore estimate our baseline model for persons at different ages (using data from ENOE and MMP) and occupational-tenure cutoffs (using data from MMP). Results are highly robust in these restricted samples (see Tables J1 and J2). In general, the fact that the selection pattern holds in very homogeneous labor markets with similar job opportunities suggests that mismatch in the sense that workers migrate *because* they lack capabilities for performing the job tasks is not a worry for us.

Figure J1: Emigrant Selection Using Occupational Skills from Different Pre-Migration Quarters



Notes: Graph shows selection on cognitive and manual skills (based on the specification in Column 4 of Table 2) using the occupational skills implied by the occupation four, three, two, or one quarter before migration. Sample consists of male Mexicans aged 16–65 who report an occupation in all four quarters previous to (potential) migration. Migrants are those individuals who are observed for four consecutive quarters before migrating in the fifth (one-fifth of the total sample). *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Table J1: Emigrant Selection on Occupational Skills:
Occupational Tenure and Age Restrictions (MMP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: migration propensity to the U.S.							
	Occupational tenure			Age			
	> 3 years	> 5 years	> 10 years	>20 years	> 25 years	> 30 years	> 35 years
Cognitive skills	–0.148***	–0.150***	–0.164***	–0.137***	–0.128***	–0.132***	–0.126***
	(0.016)	(0.017)	(0.019)	(0.017)	(0.019)	(0.022)	(0.028)
Manual skills	0.122***	0.143***	0.142***	0.096***	0.124***	0.141***	0.192***
	(0.022)	(0.023)	(0.026)	(0.024)	(0.027)	(0.032)	(0.040)
Cognitive skills × manual skills	–0.045***	–0.050***	–0.058***	–0.033***	–0.034***	–0.039***	–0.050***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.010)
Years of schooling	–0.022***	–0.025***	–0.027***	–0.020***	–0.030***	–0.035***	–0.036***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.009)	(0.010)
Age	–0.037***	–0.033***	–0.029***	–0.049***	–0.051***	–0.056***	–0.060***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Observations	454,945	438,168	388,183	409,662	338,859	268,215	202,960
Average migration rate (in %)	2.01	1.80	1.45	2.19	1.85	1.58	1.29

Notes: Sample includes Mexican males aged 16 to 65 fulfilling the occupational tenure or age restriction mentioned in the column header. Dependent variable is migrant status scaled by sample-specific annual migrant share. Average yearly migration rate is equal to 2.4%. 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 demeaned and scaled by 10. All regressions are weighted by sampling weights. 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, Mexican CONOCER, and U.S. O*NET.

Table J2: Emigrant Selection on Occupational Skills: Age Restrictions (ENOE)

	(1)	(2)	(3)	(4)	(5)
Dependent variable: migration propensity to the U.S.					
	Baseline	> 20 years	> 25 years	> 30 years	> 35 years
Cognitive skills	–0.164***	–0.166***	–0.165***	–0.167***	–0.165***
	(0.009)	(0.009)	(0.011)	(0.012)	(0.014)
Manual skills	0.182***	0.191***	0.183***	0.180***	0.188***
	(0.014)	(0.016)	(0.018)	(0.020)	(0.024)
Cognitive skills × manual skills	–0.079***	–0.081***	–0.074***	–0.070***	–0.068***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)
Years of schooling	0.010*	0.006	0.000	–0.003	0.001
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)
Age	–0.032***	–0.037***	–0.040***	–0.042***	–0.049***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Observations	2,959,528	2,631,229	2,241,222	1,869,897	1,513,343
Average migration rate (in %)	1.35	1.21	1.06	0.93	0.82

Notes: Sample includes Mexican males up to age 65 who meet the age restriction specified in the column header (*Baseline:* age 16–65). Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by sample-specific quarterly migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all previous occupations up to four quarters prior to migration. Skill measures are demeaned and scaled by 10. All regressions contain quarter-by-year fixed effects. Observations are weighted by sampling weights. Robust standard errors, shown in parentheses, are clustered at the household level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. *Data sources:* ENOE, Mexican CONOCER, and U.S. O*NET.

Second, among all occupations held by a worker in his career, the first occupation is least likely to be affected by migration decisions later in life. At the same time, plenty of evidence suggests that occupational careers are affected by early job choices.[29] Thus, we expect that the content of jobs held early in the career will be a good predictor of the content of the current job. In the MMP data, we have the opportunity to exploit long-run dynamics of occupational choices by relating an individual's first occupation to his current occupation. To do so, we therefore use occupational skills from the first occupation to instrument current occupational skills in a two-stage least squares (2SLS) model. In the second stage (Equation (J1)), we use predicted skills obtained from first-stage regressions where "current" cognitive and manual skills (calculated based on the current occupation) as well as their interaction are regressed on "first" cognitive and manual skills (calculated based on the occupation at labor-market entry) and their interaction (Equation (J2)):

$$\text{(J1)} \qquad \text{migprop}_{it} = \alpha_0 + \alpha_1 \widehat{z_{c,it}^{current}} + \alpha_2 \widehat{z_{m,it}^{current}} + \alpha_3 \widehat{z_{c,it}^{current} \times z_{m,it}^{current}} + \mathbf{X}_{\mathbf{it}}'\gamma + \zeta_t + \epsilon_{it}$$

Hence, for each $k = \{z_{c,it}^{current}, z_{m,it}^{current}, z_{c,it}^{current} \times z_{m,it}^{current}\}$, we have the following first stages:

$$\text{(J2)} \qquad k = \pi_0 + \pi_1 z_{c,it}^{first} + \pi_2 z_{m,it}^{first} + \pi_3 z_{c,it}^{first} \times z_{m,it}^{first} + \mathbf{X}_{\mathbf{it}}'\delta + \zeta_t + \nu_{i,t}$$

Table J3 contains the results of the 2SLS regressions, which are fully in line with the selection pattern in the baseline least squares models. In Column 1 (Column 2), we instrument only cognitive (manual) skills. We find that the occupational skills from the first occupation are a strong predictor of the current skill level. The coefficient is close to 0.7 and the F statistic on the excluded instrument is very large, indicating a persistent occupational pathway that is largely determined by the first occupation. Instrumenting both skills at the same time shows that current cognitive skills are predicted by cognitive skills (but not manual skills) from the first job and that current manual skills are predicted by manual skills (but not cognitive skills) from the first job (Column 3). Also, instrumenting the interaction between cognitive and manual skills does not alter the selection pattern (Column 4). These results show that occupational skills early in the career are a good approximation of skills at migration, suggesting that workers try to avoid switching to occupations that involve significant changes in job content.[30] Unless workers plan to migrate in the future already very early

[29]For instance, it is well established in the empirical labor-market literature that the probability of job change generally declines with tenure. For instance, Topel and Ward (1992) find that for men, two-thirds of all job changes happen in the first 10 years after entering the labor market. Farber (1994) shows that the job hazard rate peaks after three months of employment, and declines afterward. Abraham and Farber (1987) estimate a Weibull hazard model for job change transitions, finding that the hazard declines sharply with tenure.

[30]The selection pattern is also very similar when we estimate the baseline least squares models with occupational skill measures based on the occupation at labor-market entry.

in their careers, and choose even their first job according to the perceived returns to migration, the IV results alleviate the concern that occupational skill acquisition depends on perceived returns to these skills in the United States.

To assess the robustness of our IV specification, we add state-of-birth fixed effects as additional controls. We thus compare workers in rather homogeneous labor markets with similar job opportunities early in their careers. Table J4 shows the results. Similar to the results in Table J3, we observe that the occupational skills from the first occupation are a strong predictor of the current skill level when cognitive and manual skills enter separately (Columns 1 and 2). Reassuringly, when instrumenting both skills at the same time, current cognitive skills are predicted by cognitive skills (but not manual skills) from the first job and that current manual skills are predicted by manual skills (but not cognitive skills) from the first job (Columns 3 and 4). The second-stage results are also very similar to those in the specification without state-of-birth fixed effects; if at all, both the negative selection on cognitive skills and the positive selection on manual skills become somewhat stronger.

Clearly, there are also factors other than the current occupation through which the first occupation may affect a worker's propensity to migrate. We are thus careful to not interpret the IV results as evidence for a causal effect of a worker's skill set on his probability to migrate.

Table J3: Path Dependency in Skill Accumulation (MMP)

	(1)	(2)	(3)	(4)
Panel A: Second stage				
Dependent variable: migration propensity to the U.S.				
Cognitive skills (current occupation)	–0.148***		–0.091***	–0.183***
	(0.014)		(0.017)	(0.023)
Manual skills (current occupation)		0.239***	0.133***	0.081***
		(0.025)	(0.031)	(0.031)
Cognitive skills × manual skills (current occupation)				–0.052***
				(0.008)
Years of schooling	–0.004	–0.024***	–0.006	–0.005
	(0.008)	(0.006)	(0.008)	(0.008)
Age	–0.039***	–0.041***	–0.039***	–0.041***
	(0.002)	(0.002)	(0.002)	(0.002)
Panel B: First stage for cognitive skills				
Dependent variable: cognitive skills (current occupation)				
Cognitive skills (first occupation)	0.692***		0.689***	0.645***
	(0.010)		(0.013)	(0.017)
Manual skills (first occupation)			–0.005	–0.060***
			(0.018)	(0.018)
Cognitive skills × manual skills (first occupation)				–0.013**
				(0.006)
Kleibergen-Paap F statistics	4,794		2,411	1,611
Panel C: First stage for manual skills				
Dependent variable: manual skills (current occupation)				
Cognitive skills (first occupation)			–0.004	–0.020**
			(0.006)	(0.009)
Manual skills (first occupation)		0.694***	0.689***	0.685***
		(0.009)	(0.011)	(0.011)
Cognitive skills × manual skills (first occupation)				–0.009***
				(0.003)
Kleibergen-Paap F statistics		6,607	3,336	2,234
Panel D: First stage for cognitive skills × manual skills				
Dependent variable: cognitive skills × manual skills (current occupation)				
Cognitive skills (first occupation)				0.143***
				(0.036)
Manual skills (first occupation)				–0.306***
				(0.040)
Cognitive skills × manual skills (first occupation)				0.737***
				(0.014)
Kleibergen-Paap F statistics				1,345
Individuals	410,789	410,789	410,789	410,789

Notes: Two-stage least squares estimation (weighted by sampling weights). Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by annual migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all occupations prior to migration. Skill measures are demeaned and scaled by 10. All regressions include year fixed effects. Robust standard errors, shown in parentheses, are clustered at the individual level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Data sources:* MMP, Mexican CONOCER, and U.S. O*NET.

Table J4: Path Dependency in Skill Accumulation (MMP): Adding State-of-Birth Fixed Effects

	(1)	(2)	(3)	(4)
Panel A: Second stage				
Dependent variable: migration propensity to the U.S.				
Cognitive skills (current occupation)	–0.185***		–0.129***	–0.211***
	(0.015)		(0.019)	(0.025)
Manual skills (current occupation)		0.284***	0.134***	0.094***
		(0.026)	(0.033)	(0.033)
Cognitive skills × manual skills (current occupation)				–0.048***
				(0.009)
Years of schooling	0.014*	–0.014**	0.012	0.012
	(0.008)	(0.006)	(0.008)	(0.008)
Age	–0.041***	–0.045***	–0.042***	–0.043***
	(0.002)	(0.002)	(0.002)	(0.002)
Panel B: First stage for cognitive skills				
Dependent variable: cognitive skills (current occupation)				
Cognitive skills (first occupation)	0.677***		0.665***	0.632***
	(0.010)		(0.012)	(0.016)
Manual skills (first occupation)			–0.028	–0.034*
			(0.018)	(0.018)
Cognitive skills × manual skills (first occupation)				–0.019***
				(0.006)
Kleibergen-Paap F statistics	4,491		2,247	1,507
Panel C: First stage for manual skills				
Dependent variable: manual skills (current occupation)				
Cognitive skills (first occupation)			–0.007	–0.011
			(0.006)	(0.009)
Manual skills (first occupation)		0.670***	0.663***	0.662***
		(0.009)	(0.011)	(0.011)
Cognitive skills × manual skills (first occupation)				–0.002
				(0.003)
Kleibergen-Paap F statistics		5,831	2,952	1,990
Panel D: First stage for cognitive skills × manual skills				
Dependent variable: cognitive skills × manual skills (current occupation)				
Cognitive skills (first occupation)				0.144***
				(0.036)
Manual skills (first occupation)				–0.302***
				(0.041)
Cognitive skills × manual skills (first occupation)				0.730***
				(0.014)
Kleibergen-Paap F statistics				1,289
Individuals	410,331	410,331	410,331	410,331

Notes: Two-stage least squares estimation (weighted by sampling weights). Sample includes Mexican males aged 16–65. Dependent variable is migrant indicator (equal to 1 if migrated to the United States, and 0 otherwise) scaled by annual migrant share. Cognitive and manual skills incorporate full observed pre-migration worker history; they are defined as (unweighted) averages of skill content of current and all occupations prior to migration. Skill measures are demeaned and scaled by 10. All regressions include year fixed and birth state effects. Robust standard errors, shown in parentheses, are clustered at the individual level. Significance levels: *** p$<$0.01, ** p$<$0.05, * p$<$0.1. *Data sources:* MMP, Mexican CONOCER, and U.S. O*NET.

C Job-Switching Behavior before First Migration

Third, the MMP data allow us to assess how likely job changes (e.g., towards low-cognitive / high-manual jobs) prior to the first migration episode are. We find that in the large majority of cases (i.e., 86.6%), migrants do not change jobs in the three years before they first leave for the U.S.; in 12.4% of cases, workers change their job only once.[31] Even when extending the window to five years prior to first migration, 81.6% of the migrants do not change jobs, while 16.2% change their job once. These results indicate that the propensity to switch jobs before first migrating to the U.S. is very low, which renders unlikely that the selection pattern found in the data is driven by job choices endogenous to migration.

[31] Note that first-time migrants from Mexico to the United States are typically young – the average (median) age of first migration is 26 (24). Thus, we cannot always observe the full five years prior to migration in the MMP data. The very low propensity to change occupations during the five last pre-migration years is therefore somewhat overstated.

Appendix References

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