International Emigrant Selection on Occupational Skills

Alexander Patt, Jens Ruhose, Simon Wiederhold, and Miguel Flores*

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)

*Patt: KU Eichstätt-Ingolstadt, Auf der Schanz 49, D-85049 Ingolstadt, Germany (e-mail: alexander.patt@ku.de); Ruhose: Leibniz Universität Hannover, Königsworther Platz 1, D-30167 Hannover, Germany, CESifo, and IZA (e-mail: ruhose@wipol.uni-hannover.de); Wiederhold: KU Eichstätt-Ingolstadt (Auf der Schanz 49, D-85049 Ingolstadt, Germany), ifo Institute, and CESifo (e-mail: simon.wiederhold@ku.de); Flores: Tecnologico de Monterrey, Escuela de Gobierno y Transformación Pública, Eugenio Garza Laguera y Rufino Tamayo, San Pedro Garza Garcia, 66269, Mexico (e-mail: miguelflores@itesm.mx). We thank George J. Borjas, David Deming, Benjamin Elsner, Jesús Fernández-Huertas Moraga, David Figlio, Lawrence Kahn, Marc Piopiunik, Andreas Steinmayr, seminar participants at Freiburg, Passau, and Trier, as well as participants at the 2016 meeting of the American Economic Association in San Francisco, the 13th IZA Annual Migration Meeting in Bonn, the 2016 meeting of the German Economic Association in Augsburg, the 2017 meeting of the standing field committee "Education Economics" of the German Economic Association in Hanover, and the 2017 CESifo Area Conference "Economics of Education" for helpful comments. We are also grateful to Jesús Fernández-Huertas Moraga for sharing his code for cleaning the ENET data. Patt, Wiederhold, and Flores are thankful for the hospitality provided by the Center for International Development at Harvard University, with special thanks to Ricardo Hausmann, Ljubica Nedelkoska, and Frank Neffke. Wiederhold gratefully acknowledges the receipt of a scholarship from the Fritz Thyssen Foundation for financing the research stay at Harvard University. Patt and Wiederhold also gratefully acknowledge financial support from the European Union's (Grant agreement no. 290683) FP7 through the LLLight'in'Europe project.

I Introduction

The worldwide stock of international migrants amounts to 244 million people (equivalent to 3.3% of the world population), having increased by almost 60% over the last 25 years (United Nations, 2015). International migration is often directed toward developed countries. Between 1990 and 2015, the population share of international migrants in developed countries has increased from 7.2% to 11.2%. Moreover, a substantial share of these moves is work related.[1] Because international migrants make up a sizable 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 Online 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 and better interpretable than earnings, which presumably reflect all sorts of observed and unobserved inputs (e.g., ability, family background, school quality, on-the-job training, etc.).

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 to group occupations by *multiple* skills.[4] This provides a more nuanced picture of the selectivity

[1]Recent estimates suggest that one-half of all migration movements to OECD countries are for work-related reasons (OECD, 2016). 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).

[4]The task framework takes into account that there are large differences in the skill requirements of occupations

of migrants because one-dimensional skill measures can yield results that are difficult to interpret or even misleading if positive and negative selection on different skill dimensions occur jointly (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 the role of occupational skills in emigrant selection, 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] Principal component analysis shows that the occupational skill space in Mexico can be expressed 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] 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 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

within commonly used occupational categories (e.g., the blue/white collar dichotomy) (Ingram and Neumann, 2006; Poletaev and Robinson, 2008; Yamaguchi, 2012; Robinson, 2017). 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]In fact, previous studies 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 (Gould and Moav, 2016). Parey et al. (2017) is one of the few papers that considers multiple skills by systematically investigating which components of predicted earnings explain emigrant selection.

[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).

in O*NET, and *(ii)* using the loadings obtained from O*NET data when constructing CONOCER-based skills.

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).[8] 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 experienced 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 the 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 shoemaker to a medical technician).

The observed pattern of selection on occupational skills 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 (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.[9] 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

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

[9]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.

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. Most recently, 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.

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 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). Any positive relationship between differential returns to skills and migration therefore reflects 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.

We check the robustness of our results in various ways. For instance, we find a similar selection pattern for each education level of Mexican workers. Thus, our results are not just driven by low-educated workers who used to be employed in high-manual low-cognitive jobs in Mexico and work in similar manual-task-intensive jobs in the United States. However, the selection pattern is by far the weakest for tertiary-educated Mexicans, partly reflecting their generally low migration propensity. Moreover, having information on the worker history allows us to account for the possibility that the last pre-migration occupation is endogenous to the migration decision, for instance, because a negative labor-market shock forces workers to enter a less desirable occupation and pushes them to migrate. We also show that the selection pattern is not just due to temporary and seasonal migrants, who are often lower educated than permanent migrants (Hanson, 2006).

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. However, we also consider the possibility that Mexican workers are imperfectly matched to their current job by exploiting information on the individual's occupation at the start of his career in an instrumental-variable analysis. These models suggest 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 tend to switch to skill-related occupations both within Mexico and when migrating to the United States. Our results are also very similar for high-tenured workers who are less likely to suffer from imperfect job-worker matching. Finally, 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 does not affect our findings.

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 V provides evidence that returns to occupational skills are crucial for understanding economic benefits to migration and for explaining selection on earnings. Section VI 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 (*responsibility*, *knowledge*, *tools*, *abilities*, *social skills*, *traits*, *skills,* and *physical abilities*) 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).[10] 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").[11] In order to create a measure of the average 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 the United States and Mexico may represent very different skill requirements in some cases—for instance, a cashier in Mexico may need more manual skills than a cashier in the United States, whose job is more computerized. (We describe in detail below why our analysis requires comparability of skill measures between Mexico and the United States.)

While the number of variables included in worker surveys is generally large, it is unlikely that all of them measure separate skills. Given that responses in subsets of questions are often highly correlated, they in fact represent related information content, which can be summarized by a small number of underlying constructs. Each such construct is obtained by a principal component analysis (PCA) of the responses to seemingly related questions.[12] For example, questions on active learning, proactivity, and problem solving—while worded differently in CONOCER—appear to represent the same skill dimension (i.e., cognitive skills). Moreover, by applying PCA, we are not forced to make subjective judgments to identify questions from the survey that represent a specific skill, which also alleviates the problem that questions differ in how reliably they measure

[10] 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.

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

[12] 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 to O*NET. Yamaguchi (2012) and Autor and Handel (2013) employ PCA to create similarly constructed measures of job tasks.

underlying dimensions of skills.

Both CONOCER and O*NET are designed with the purpose of primarily measuring cognitive, manual, and interpersonal skills. We therefore focus on sets of questions that are related to these skills and use the variation in responses to extract corresponding skill measures. This is facilitated by the design of CONOCER, which organizes its questions by content. We create a correspondence between the questions in CONOCER and O*NET by selecting questions that are worded similarly in both surveys and organizing them into five major groups by content relatedness (i.e., *use of tools*, *physical skills, cognitive & social skills*, *traits*, and *use of office equipment*). The advantage of working with separate groups of related questions is that this does not impose an arbitrary assumption of orthogonality of skill measures. Applying PCA separately in each group, we find that the first principal components capture 50–95% of the variation, and thus provide an efficient summary of the data. However, even after this data reduction step, there remains substantial shared variance between the reduced measures of each group (obtained from the first principal components). We therefore repeat the PCA on the reduced variables, which leads to two skill dimensions. We take the first principal component of reduced variables for *use of tools* and *physical skills* as a measure of manual skills. We take the first principal component of reduced variables for *cognitive & social skills, traits,* and *use of office equipment* as a measure of cognitive skills.

In constructing the Mexican skill measures, we follow a procedure that makes them exactly comparable to similarly constructed skill measures for the United States.[13] Thus, one unit of skill in Mexico has the same interpretation as one unit of the same skill in the United States, which 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). Comparability of the skill measures is achieved by (a) using similarly worded questions from both surveys,[14] (b) having the same response scale for the questions (by virtue of the similarity in survey design between CONOCER and O*NET), and (c) using loadings from the analysis of one survey (which we chose to be O*NET) to calculate the scores for each domain in both surveys. The fact that loadings obtained from separate analyses of O*NET and CONOCER are generally very similar (see Online Appendix C) suggests that the variables in both surveys measure similar skill dimensions, making our approach feasible. 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. This provides occupational skill measures that are directly comparable across borders.

[13]Online Appendix C explains in detail how we construct comparable skill measures in CONOCER and O*NET. 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).

[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 provide scores highly correlated with those constructed from the subset of questions ($\rho > 0.86$).

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: $\rho = -0.56$), but we also see plenty of variation in the other skill for a given level of cognitive or manual skills.[15]

Figure 1 also illustrates that the average Mexican worker, relative to his peers 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.[16] There are several potential reasons for the compressed manual skill distribution in Mexico. First, the skill-biased employment structure in the United States could have led to the creation of (labor-intensive) jobs that are not available in Mexico. For example, the high opportunity cost of skilled workers in the United States to perform simple tasks results in a market for services that are close substitutes for home production activities (personal care services, housekeeping, etc.) (Cortés and Tessada, 2011; Mazzolari and Ragusa, 2013). Second, but related to the first argument, task specialization among natives and migrants leads to an expansion of occupations with high cognitive skill intensity among natives and high manual skill intensity among migrants (Peri and Sparber, 2009; Peri, 2012), increasing the variance in occupational skills.[17] Third, 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 man-

[15] Both occupational skill measures also vary widely for a given year of schooling (see Figure A1(a) in the Online Appendix). 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 Figure A1(b) in the Online Appendix). Thus, there is considerable variation in cognitive and manual skills both at the bottom and at the top of the earnings distribution.

[16] Overall percentile ranges of occupational skills in the Mexican worker surveys (described below) are very similar.

[17] For example, using the U.S. Census 2000, we find that agricultural workers and construction workers have manual scores above the 90th percentile; these occupations have manual scores around the 70th percentile in Mexico. Even though it is difficult to compare occupations across borders because they differ in their specific contents and requirements, this could mean that Mexican migrants have higher manual skills than the average worker in their previous occupation in Mexico and/or that migrants work in occupations in the United States that require higher manual skills than the occupation previously held in Mexico. We discuss the implications of skill mismatch and partial skill transferability in Section III.

ual 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, PCA seems to yield a sensible classification of jobs along the two skill dimensions.[18] Second, even within the top-six and bottom-six occupations, there is some variation in the skills of the other skill 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, households are surveyed for five consecutive quarters and the survey reports socio-demographic variables, such as age, gender, educational attainment, occupation, and earnings of (documented and undocumented) migrants and non-migrants. Importantly, the panel structure of the survey allows the identification of emigrant characteristics before the move.

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 those 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).

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.[19] In further analysis, we check the robustness of our results in three other surveys that are

[18] 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 Online Appendix C for details and a discussion.

[19] 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. De-

also commonly used to identify Mexican migrants (see Online 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, 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 measures of cognitive and manual skills use all occupational information available in the data, that is, they incorporate the full observed pre-migration worker history (see Yamaguchi, 2017, for a similar approach to measure worker endowment of task-specific skills). In ENOE and ENET, where we have at most four pre-migration quarters, we use average occupational skills over all available quarters prior to migration to measure migrant skills. In MMP, where we have information on an individual's complete job history, we take the average of occupational skills over the entire pre-migration history to construct the skill measures. In MxFLS, we take the average of the current job, the job five years prior to the survey, and the first job.[20]

Relying not only on the task content of the current job, but on the history of past tasks, 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 immediately clear which occupation is most appropriate for measuring occupational skills. The last pre-migration occupation is endogenous to the migration move if individuals regard it as particularly suitable for emigration (e.g., for visa considerations). 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). Using an average over all observed occupations seems to be an appropriate way of capturing a worker's actual occupational skills, at the same time alle-

tails are provided in Online Appendix D.B.

[20]In Online 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).

viating concerns about the endogeneity of the pre-migration occupation. Third, using a cumulative skill measure allows us to consider individuals who are unemployed in the current period.[21] 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. 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).[22] 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 Online 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.[23] In line with the basic variant of the Roy/Borjas model, we show 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

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

[22] To the best of our knowledge, there are no data that would allow us to measure the occupational skill level of migrants *within* an occupation.

[23] 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 the migration decision.

United States to derive model 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:

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

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[24] and occupations, tasks, and skills are interchangeable.[25]

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:

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

where $\mathbf{p}^j$ is a vector of returns to skills or returns to tasks (equivalently, skill or task prices)[26] 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 distribution of skills.)[27] From these assumptions, it follows that workers in more task-intensive

[24]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.B) and due to skill-specific labor-market shocks or imperfect job matches early in the career (Online Appendix G.C). The analysis shows that skill mismatch is unlikely to affect our results.

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

[26]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.

[27]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

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. 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. Migration costs are the same for all migrants. 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 $\beta_{2,1} = \operatorname{Cov}(z_1, z_2)/\operatorname{Var}(z_1)$ is the slope of a least squares regression of skill 2 on skill 1, $d = (\kappa - \lambda_1\mu_1 - \lambda_2\mu_2)/\sigma$, $\sigma^2 = \operatorname{Var}(\lambda_1 z_1 + \lambda_2 z_2)$, and $\phi(d)/[1 - \Phi(d)]$ is the inverse Mills ratio.[28] 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

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.

[28] See Online 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 $\lambda_2 = -1$.

relocating one unit of skill 1 abroad. 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.[29] 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 $\beta_{2,1} < 0$).[30] 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 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

[29] 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).

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

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).

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, 2017). 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- and post-migration occupations (Chiswick et al., 2005; Akresh, 2008; Hendricks and Schoellman, 2017). We use the MMP for this comparison, because respondents report their entire occupational history (also during migration episodes). Occupational switching of immigrants is widespread; two-thirds of 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 occupational switchers amounts to 57% (54%).[31]

However, these occupational switches are not systematically related to changes in the quality of jobs, measured by their skill content.[32] 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.[33] 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.[34]

[31]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, 2017).

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

[33]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.

[34]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,

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 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 shows 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).[35] 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.[36]

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 Online 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 skillsof U.S. natives or with certain high-paid cognitive jobs being unavailable for Mexican migrants (e.g., due to

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.

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

[36] 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.

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 potential earning prospects based on observable returns of former Mexican migrants (Kaestner and Malamud, 2014). We return to this issue in Section V.

IV Results

This section compares the occupational skills of migrants and non-migrants in the quarter prior to migration. In line with the theory presented in Section III, the evidence shows that migrants from Mexico to the United States are generally positively selected on manual skills and negatively selected on cognitive skills. In Section IV.A, we follow the previous selection literature by comparing migrants to non-migrants at the national level. Section IV.B provides a natural extension of this 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).

A Selection of Emigrants on Occupational Skills

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 population 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.[37] This shows that migrants are negatively selected on cognitive skills along the entire skill distribution. For manual skills, we find that the CDF of migrants is to the right of the CDF of non-migrants, indicating positive selection. These results are confirmed by the PDFs, showing that the mass of

[37] Kolmogorov-Smirnov tests indicate that the CDFs for both cognitive and manual skills are significantly different from each other throughout.

density for Mexican migrants is at the bottom (top) of the cognitive (manual) skill distribution.[38] 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).[39] 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. This indicates that Mexican emigrants to the United States are negatively selected in terms of cognitive skills and positively selected in terms of manual skills. 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 A2).[40]

Appendix Table A1 also reports the 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 the educational selection of emigrants. 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).

These comparisons, however, do not reveal whether individuals' occupational skills 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. We estimate the model as a pooled cross-section and include quarter-by-year fixed effects to account for temporal migration shocks. 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 the interaction between cognitive and manual skills, which allows for a nonlinear relation of skills with migration propensity.[41] The coefficients on cognitive

[38]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.

[39]Because the probability of Mexicans moving to the United States differs substantially across time (due to different migration waves) and across datasets (due to different sampling frames), we scale the migration indicator by the average migration rate to make effect sizes comparable. That is, the migration indicator shows the probability of migrating as a percentage of the average migration rate. Using an unscaled migration indicator leads to equivalent results.

[40]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.

[41]To facilitate interpretation, we de-mean cognitive and manual skills in the interacted models; that is, the marginal

and manual skills change only slightly when adding an interaction of both skill domains, which itself turns out to be negative (Column 2).[42]

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). This suggests that the negative selection on education commonly found in other studies operates through the selection on occupational skills. Put differently, holding the occupational skills constant, people with better education are not less likely to migrate. This result is consistent with the work by Villarreal (2016) showing that Mexican migrants are positively selected on education within broader occupational groups.

The selection on occupational skills is not only statistically significant, it is also economically relevant. In our baseline specification (Column 4), 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 the migration propensities of a shoemaker (at the mean of the cognitive skill distribution) and a medical technician ($+1$ decile in cognitive skills). Similarly, when manual skills increase by one decile, the propensity to migrate increases by 18%. This is equivalent to comparing the 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 (shown in Column 4). 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).

We can also define labor markets in terms of broader occupational categories. Column 7 of Table 2 shows that the results are not just driven by differences in the job content of large occupa-

effect of either skill is evaluated at the mean of the other skill.

[42] Instead of using an interaction between cognitive and manual skills, we also estimate specifications that control for the impact of the other occupational skill on the migration propensity by adding a sixth-order polynomial or decile fixed effects. The selection pattern is very similar to that in the baseline model (see Appendix Table A2).

tional 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 current 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-task-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-task-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 3, 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 negatively selected on cognitive skills at each education level, which rules out that low-educated migrants with high-manual low-cognitive jobs in Mexico drive our results. However, the selection pattern is by far the weakest for individuals with more than twelve years of schooling (i.e., tertiary education). This result is related to the fact that migration propensity is lowest for tertiary-educated workers (compared to workers with any other education) because they have the least incentive to migrate.

Online Appendix G contains further analysis of the robustness of the selection pattern. We provide results for different datasets, by migration status, and for permanent migrants only. Because Mexican migrants to the United States have often worked in agriculture before migrating, we show specifications in which agricultural workers are dropped. To further address seasonal migration, we investigate whether selection on occupational skills follows any seasonal pattern. We also check whether our results are affected by imperfect job matches due to skill-specific labor-market shocks right before migration or early-career skill mismatch. To account for the possibility that there are more permanent frictions in the matching of workers to jobs, we exploit long-run dynamics of occupational choices, using an individual's occupation at labor-market entry as an instrument for his current occupation. Our results are remarkably robust across these various specifications. Finally, we investigate the long-run dynamics of selection on occupational skills of Mexico-U.S. migrants. Exploiting the fact that some of our worker data reach 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 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: the migration propensity of cooks is more than 50% higher than the 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 (e.g., 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-versus-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 4). This specification compares the 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 the 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 4 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. Even 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. 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 the 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 earnings (see Online 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 5, Column 1 of Panel B), translating into a strong negative mean selection on log hourly earnings (Column 1 of Panel A).[43]

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.[44] 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.[45] First, we 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).[46] Second, based on the predicted earnings for Mexican residents and for Mexican migrants, we construct labor-market returns for each skill 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.

[43]Following Chiquiar and Hanson (2005) and Fernández-Huertas Moraga (2011), hourly earnings are obtained by dividing monthly earnings by 4.5 $\times$hours worked per week. Earning 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 earning observations are dropped. Earnings are converted into PPP-adjusted U.S. dollars using OECD PPP-adjusted exchange rates and then denoted in real 2010 U.S. dollars using U.S. CPI data.

[44]This restricts any analysis to those characteristics that can be equivalently measured in the Mexican and U.S. data.

[45]Appendix Tables A3 and A4 show that results are robust to using differential returns based on the 2010 ACS.

[46]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).

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 5). Increasing differential basic returns by 1, 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 earning quintiles (Panel B) decrease in absolute size compared to the specification without basic returns. For example, a doubling of log hourly earnings is only associated with a decrease in migration propensity by 17% (instead of 33.5%) and migration propensity drops from 72% to 38% for the highest quintile versus 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 returns (Column 3 of Table 5). 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. 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 5, we add the travel distance to the U.S. border as a proxy for the cost of migration. In line with previous results, including migration costs leads to slightly more pronounced selection on earnings. However, it does not affect the impact of differential returns on earnings selection.

In Online 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 even become 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 study migrant selection within 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 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 6, we replicate the specifications from Table 5 within narrow labor markets; that is, we compare migrants and non-migrants within the same broader occupational group working in the same industry, year, and residence state (see Column 4 of Table 4). 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 6), and there is little, if any, selection along the earnings distribution (Panel B of Table 6). 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 6 show that differential returns to occupational skills remain to be positively related to the 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 5 and 6). In contrast, the coefficients on differential returns to basic skills, which are positively related to migration at the national level, turn negative now. 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 4).

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 the same 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 Conclusions

International migrants constitute a sizable fraction of the labor force in many countries. Therefore, understanding who migrates and why is essential for informed labor-market and migration policies in sending and receiving countries. In this paper, we provide the first evidence how migrants and non-migrants differ in 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. We find 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 over and above its effect on occupational choice. In line with this result, we find that the benefits of migration originate from occupational choices and acquired skills and not from worker characteristics like education and age emphasized in previous work.

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 suggests 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.

In light of these results, collecting data on job tasks in other emigration countries to study the selection on occupational skills for a wide range of migration flows would provide an important building block toward better understanding migration behavior.

References

Abramitzky, R., Boustan, L. P., and Eriksson, K. (2012). Europe's Tired, Poor, Huddled Masses: Self-Selection and Economic Outcomes in the Age of Mass Migration. *American Economic Review*, 102(5):1832–1856.

Acemoglu, D. and Autor, D. H. (2011). Skills, Tasks, and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D. E., editors, *Handbook of Labor Economics Volume 4*, volume 4B. Amsterdam: Elsevier.

Akresh, I. R. (2008). Occupational trajectories of legal us immigrants: Downgrading and recovery. *Population and Development Review*, 34(3):435–456.

Almlund, M., Duckworth, A. L., Heckman, J. J., and Kautz, T. (2011). Personality Psychology and Economics. In Hanushek, E. A., Machin, S., and Woessmann, L., editors, *Handbook of the Economics of Education*, chapter 1, pages 1–181. Elsevier, 4 edition.

Altonji, J. G. and Pierret, C. R. (2001). Employer Learning and Statistical Discrimination. *Quarterly Journal of Economics*, 116(1):313–350.

Ambrosini, J. W. and Peri, G. (2012). The Determinants and the Selection of Mexico-US Migrants. *World Economy*, 35(2):111–151.

Autor, D. (2013). The "Task Approach" to Labor Markets: An Overview. *Journal for Labour Market Research*, 46(3):185–199.

Autor, D. and Dorn, D. (2013). The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market. *American Economic Review*, 103(5):1553–1597.

Autor, D. and Handel, M. (2013). Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics*, 31(2):S59–S96.

Autor, D., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118(4):1279–1333.

Bazzi, S., Gaduh, A., Rothenberg, A. D., and Wong, M. (2016). Skill Transferability, Migration, and Development:Evidence from Population Resettlement in Indonesia. *American Economic Review*, 106(9):2658–2698.

Borjas, G. J. (1987). Self-Selection and the Earnings of Immigrants. *American Economic Review*, 77(4):531–553.

Borjas, G. J. (1991). Immigration and Self-Selection. In Abowd, J. M. and Freeman, R. B., editors, *Immigration, Trade and the Labor Market*, chapter 1, pages 29–76. University of Chicago Press.

Borjas, G. J. (1994). The Economics of Immigration. *Journal of Economic Literature*, 32(4):1667–1717.

Borjas, G. J. (2003). The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market. *Quarterly Journal of Economics*, 118(4):1335–1374.

Cadot, O., Carrère, C., and Strauss-Kahn, V. (2011). Export Diversification: What's Behind the Hump? *Review of Economics and Statistics*, 93(2):590–605.

Chiquiar, D. and Hanson, G. H. (2005). International Migration, Self-Selection, and the Distribution of Wages: Evidence from Mexico and the United States. *Journal of Political Economy*, 113(2):239–281.

Chiswick, B. R., Lee, Y. L., and Miller, P. W. (2005). A longitudinal analysis of immigrant occupational mobility: A test of the immigrant assimilation hypothesis. *International Migration Review*, 39(2):332–353.

Cortes, P. (2008). The effect of low-skilled immigration on u.s. prices: Evidence from cpi data. *Journal of Political Economy*, 116(3):381–422.

Cortés, P. and Tessada, J. (2011). Low-Skilled Immigration and the Labor Supply of Highly Skilled Women. *American Economic Journal: Applied Economics*, 3(3):88–123.

Dahl, G. B. (2002). Mobility and the Return to Education: Testing a Roy Model with Multiple Markets. *Econometrica*, 70(6):2367–2420.

Dustmann, C., Fadlon, I., and Weiss, Y. (2011). Return Migration, Human Capital Accumulation and the Brain Drain. *Journal of Development Economics*, 95(1):58–67.

Dustmann, C., Frattini, T., and Preston, I. P. (2013). The Effect of Immigration Along the Distribution of Wages. *Review of Economic Studies*, 80(1):145–173.

Dustmann, C. and Glitz, A. (2011). Migration and Education. In Hanushek, E. A., Machin, S., and Woessmann, L., editors, *Handbook of the Economics of Education*, chapter 4, pages 327–439. Elsevier, 4 edition.

Dustmann, C. and Preston, I. (2012). Comment: Estimating the Effect of Immigration on Wages. *Journal of the European Economic Association*, 10(1):216–223.

Dustmann, C., Schönberg, U., and Stuhler, J. (2016). The Impact of Immigration: Why Do Studies Reach Such Different Results? *Journal of Economic Perspectives*, 30(4):31–56.

Fernández-Huertas Moraga, J. (2011). New Evidence on Emigrant Selection. *Review of Economics and Statistics*, 93(1):72–96.

Fernández-Huertas Moraga, J. (2013). Understanding Different Migrant Selection Patterns in Rural and Urban Mexico. *Journal of Development Economics*, 103(1):182–201.

Firpo, S., Fortin, N., and Lemieux, T. (2011). Occupational Tasks and Changes in the Wage Structure. IZA Discussion Paper No. 5542.

Friedberg, R. M. (2000). You Can't Take It with You? Immigrant Assimilation and the Portability of Human Capital. *Journal of Labor Economics*, 18(2):221–251.

Gathmann, C. and Schönberg, U. (2010). How General is Human Capital? A Task-Based Approach. *Journal of Labor Economics*, 28:1–50.

Gibbons, R. S. and Waldman, M. (2004). Task-Specific Human Capital. *American Economic Review*, 94(2):203–207.

Gould, E. D. and Moav, O. (2016). Does High Inequality Attract High Skilled Immigrants? *Economic Journal*, 126(593):1055–1091.

Hanson, G. H. (2006). Illegal Migration from Mexico to the United States. *Journal of Economic Literature*, 44(4):869–924.

Hanson, G. H. and McIntosh, C. (2010). The Great Mexican Emigration. *Review of Economics and Statistics*, 92(4):798–810.

Hanushek, E. A., Schwerdt, G., Wiederhold, S., and Woessmann, L. (2015). Returns to Skills Around the World: Evidence from PIAAC. *European Economic Review*, 73(C):103–130.

Heckman, J. J., Lochner, L. J., and Todd, P. E. (2006). Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond. In Hanushek, E. A. and Welch, F., editors, *Handbook of the Economics of Education*, volume 1, pages 307–458. Amsterdam: North Holland.

Heckman, J. J. and Scheinkman, J. (1987). The Importance of Bundling in a Gorman-Lancaster Model of Earnings. *Review of Economic Studies*, 54(2):243–255.

Hendricks, L. and Schoellman, T. (2017). Human capital and development accounting: New evidence from wage gains at migration. *Quarterly Journal of Economics*, Forthcoming.

Imbs, J. and Wacziarg, R. (2003). Stages of Diversification. *American Economic Review*, 93(1):63–86.

Ingram, B. F. and Neumann, G. R. (2006). The Returns to Skill. *Labour Economics*, 13(1):35–59.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, 83:685–709.

Jovanovic, B. (1979). Job Matching and the Theory of Turnover. *Journal of Political Economy*, 87(5):972–990.

Kaestner, R. and Malamud, O. (2014). Self-Selection and International Migration: New Evidence from Mexico. *Review of Economics and Statistics*, 96(1):78–91.

Kambourov, G. and Manovskii, I. (2009). Occupational Specificity of Human Capital. *International Economic Review*, 50(1):63–115.

Kennan, J. and Walker, J. R. (2011). The Effect of Expected Income on Individual Migration Decisions. *Econometrica*, 79(1):211–251.

Kok, S. and ter Weel, B. (2014). Cities, Tasks and Skills. CPB Discussion Paper No. 269.

Mazzolari, F. and Ragusa, G. (2013). Spillovers from High-Skill Consumption to Low-Skill Labor Markets. *Review of Economics and Statistics*, 95(1):74–86.

McKenzie, D. and Rapoport, H. (2010). Self-Selection Patterns in Mexico-U.S. Migration: The Role of Migration Networks. *Review of Economics and Statistics*, 92(4):811–821.

Neal, D. (1995). Industry-Specific Human Capital: Evidence from Displaced Workers. *Journal of Labor Economics*, 13(4):653–677.

Nedelkoska, L., Neffke, F., and Wiederhold, S. (2017). Skill Mismatch and the Costs of Job Displacement. Mimeo.

OECD (2016). International Migration Outlook 2016. Paris: OECD Publishing. `http://dx.doi.org/10.1787/migr_outlook-2016-en`.

Orrenius, P. M. and Zavodny, M. (2005). Self-Selection Among Undocumented Immigrants from Mexico. *Journal of Development Economics*, 78(1):215–240.

Parent, D. (2000). Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics. *Journal of Labor Economics*, 18(2):306–323.

Parey, M., Ruhose, J., Waldinger, F., and Netz, N. (2017). The Selection of High-Skilled Emigrants. *Review of Economics and Statistics*, forthcoming.

Peri, G. (2012). The Effect of Immigration on Productivity: Evidence from U.S. States. *Review of Economics and Statistics*, 94(1):348–358.

Peri, G. (2016). Immigrants, Productivity, and Labor Markets. *Journal of Economic Perspectives*, 30(4):3–30.

Peri, G. and Sparber, C. (2009). Task Specialization, Immigration, and Wages. *American Economic Journal: Applied Economics*, 1(3):135–169.

Poletaev, M. and Robinson, C. (2008). Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys. *Journal of Labor Economics*, 26(3):387–420.

Rendall, M. S. and Parker, S. W. (2014). Two Decades of Negative Educational Selectivity of Mexican Migrants to the United States. *Population and Development Review*, 40(3):421–446.

Robinson, C. (2017). Occupational mobility, occupation distance and specific human capital. *Journal of Human Resources*, Forthcoming.

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers*, 3(2):135–146.

Sjaastad, L. A. (1962). The Costs and Returns of Human Migration. *Journal of Political Economy*, 70(5):80–93.

United Nations (2015). Trends in International Migrant Stock: The 2015 Revision (United Nations database, POP/DB/MIG/Stock/Rev.2015).

Villarreal, A. (2016). The Education-Occupation Mismatch of International and Internal Migrants in Mexico, 2005-2012. *Demography*, 53(3):865–883.

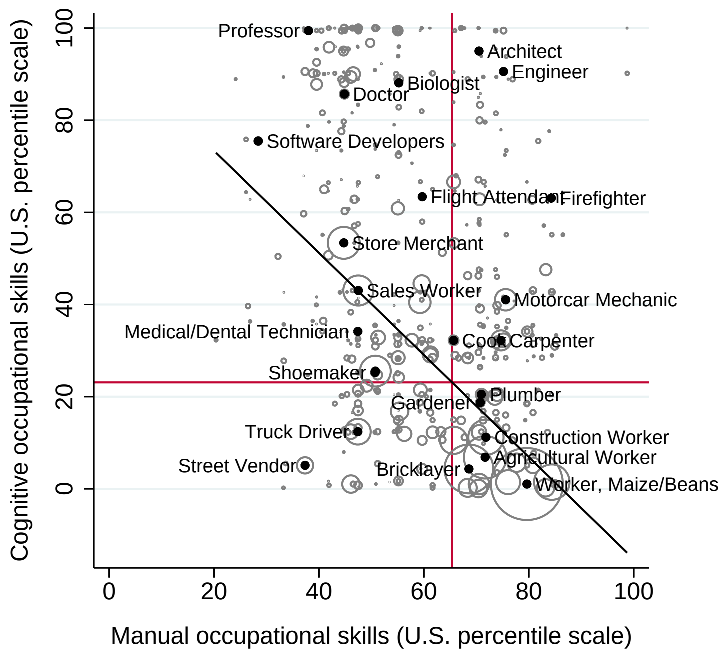
Welch, F. (1969). Linear Synthesis of Skill Distribution. *Journal of Human Resources*, 4(3):311–327.

Yamaguchi, S. (2012). Tasks and Heterogeneous Human Capital. *Journal of Labor Economics*, 30(1):1–53.

Yamaguchi, S. (2017). Changes in returns to task-specific skills and gender wage gap. *Journal of Human Resources*, forthcoming.

Figures and Tables

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

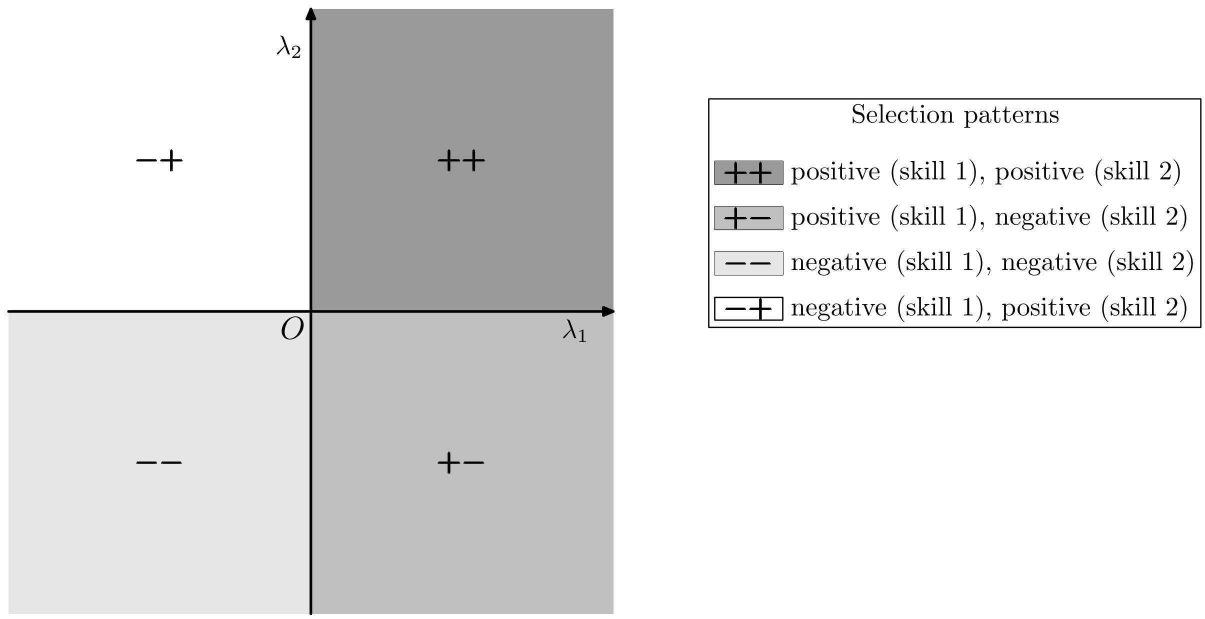


Notes: Figure plots cognitive and manual occupational skills in the Mexican population, measured in U.S. 2010 percentile ranks and weighted by the number of observations in the Mexican Census 2010. Sample restricted to male Mexicans aged 16–65. Regression line (black) is weighted by numbers of observations. Red lines show weighted averages of cognitive and manual occupational skills. The weighted correlation between the skills is $\rho = -0.56$ and the unweighted (i.e., occupation-level) correlation is $\rho = -0.19$. *Data sources:* CONOCER and Mexican Census 2010.

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

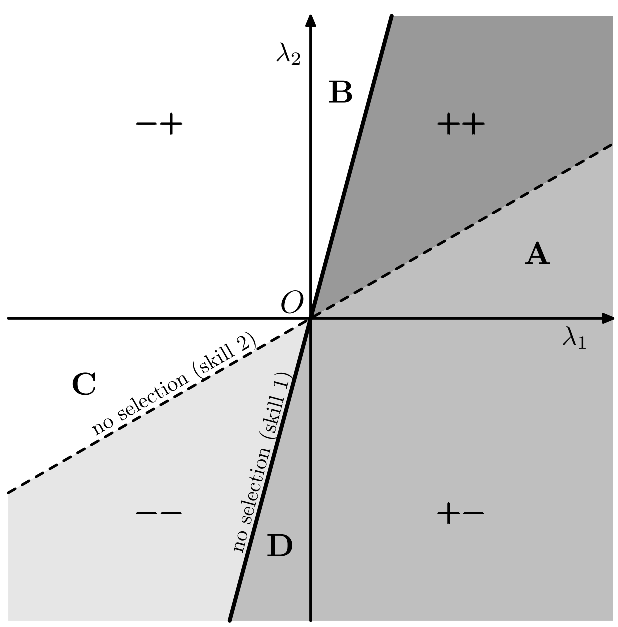
(a) Zero Correlation Between Skills

$\rho = 0$



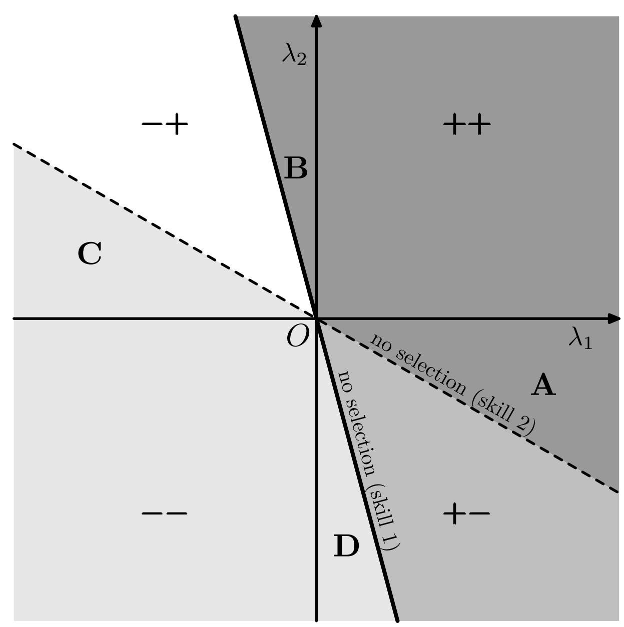
(b) Negative Correlation Between Skills

$\rho < 0$



(c) Positive Correlation Between Skills

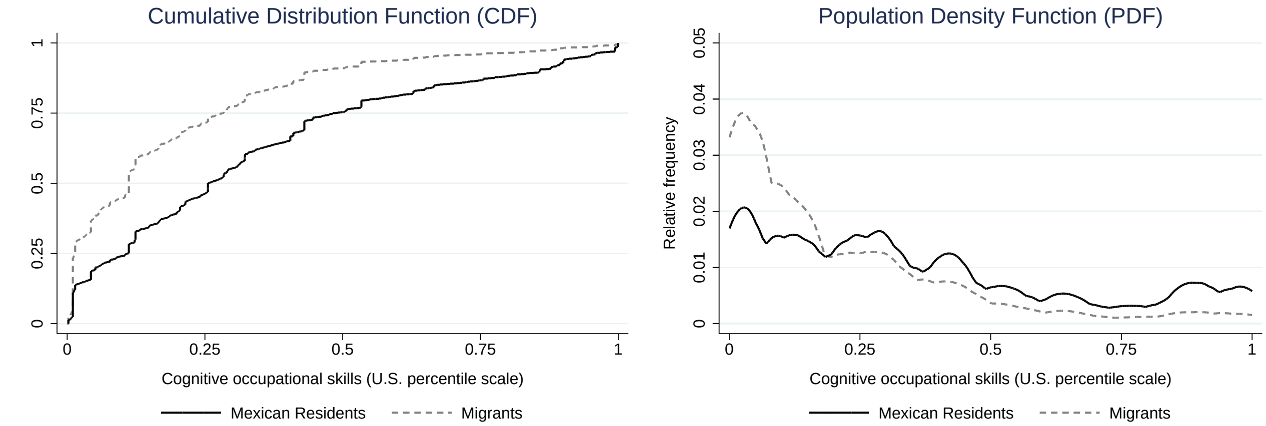
$\rho > 0$



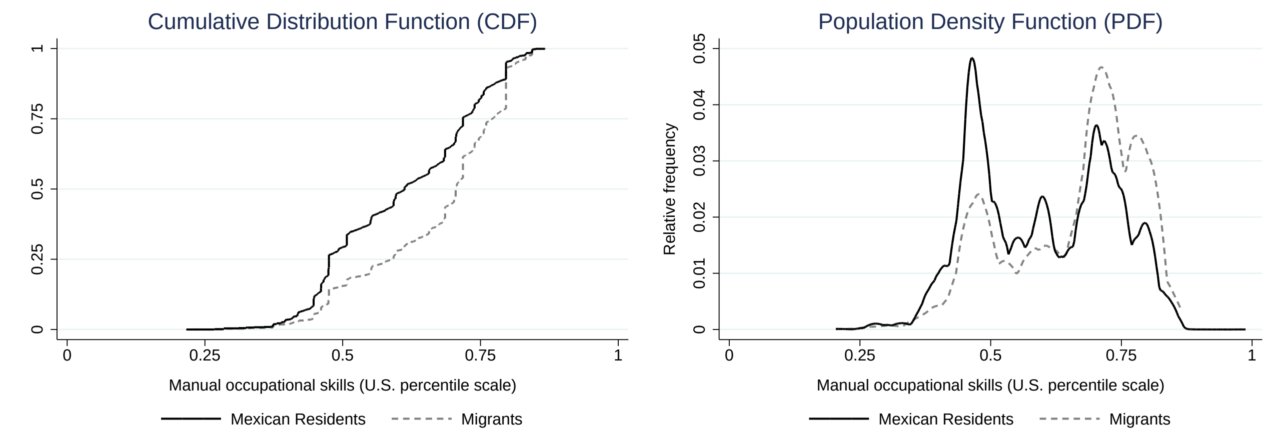
Notes: Figure shows the predictions of the two-dimensional Roy/Borjas model (Section III.A) when skill 1 and skill 2 are uncorrelated (Figure 2(a)), negatively correlated (Figure 2(b)), or positively correlated (Figure 2(c)). Regions are defined as follows: "++" for positive selection on both skills; "+−" 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 population 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 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:* CONOCER and ENOE.

Table 1: Skill Content of Mexican Occupations

Panel A: Top 6 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 6 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. Scores and percentiles give the position in the U.S. 2010 occupational skill distribution. See text for details. *Data sources:* CONOCER and Mexican Census 2010.

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

Dependent variable: migration propensity to the U.S.							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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. 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:* CONOCER and ENOE.

Table 3: Emigrant Selection on Occupational Skills: Results by Years of Schooling

Dependent variable: migration propensity to the U.S.						
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	0–3 years	4–6 years	7–9 years	10–12 years	> 12 years
Cognitive skills	–0.164***	–0.086***	–0.137***	–0.246***	–0.175***	–0.051***
	(0.009)	(0.026)	(0.027)	(0.016)	(0.016)	(0.015)
Manual skills	0.182***	0.168***	0.153***	0.162***	0.119***	0.052
	(0.014)	(0.051)	(0.045)	(0.025)	(0.030)	(0.040)
Cognitive skills × manual skills	–0.079***	–0.019	–0.099***	–0.152***	–0.074***	–0.016*
	(0.005)	(0.020)	(0.019)	(0.012)	(0.012)	(0.009)
Years of schooling	0.010*	0.165***	0.052	0.061	0.076	0.032
	(0.005)	(0.039)	(0.068)	(0.068)	(0.053)	(0.020)
Age	–0.032***	–0.032***	–0.047***	–0.033***	–0.019***	–0.018***
	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	2,959,528	300,246	579,752	859,959	625,085	594,486

Notes: Sample includes Mexican males up to age 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 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:* CONOCER and ENOE.

Table 4: Emigrant Selection on Occupational Skills: Results Within Narrow Labor Markets

Dependent variable: migration propensity to the U.S.				
	(1)	(2)	(3)	(4)
	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. 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:* CONOCER and ENOE.

Table 5: 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 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:* CONOCER, ENOE, Mexican Census 2000 (10.6% sample), and U.S. Census 2000 (5% sample).

Table 6: 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)

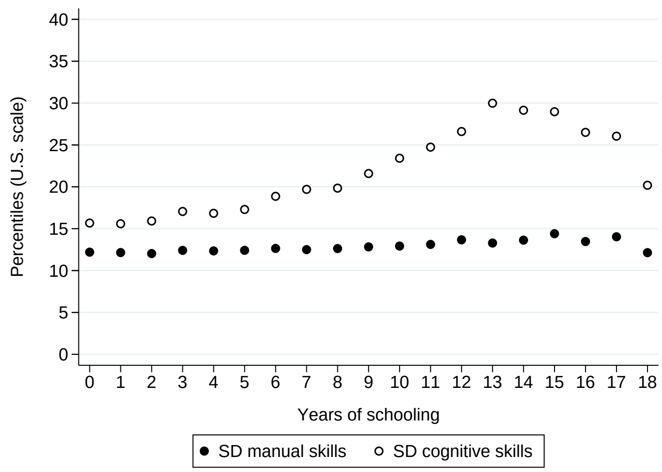
Notes: Table shows results analogous to those in Table 5 within 226,197 labor-market segments at the occupation $\times$ year $\times$ state $\times$ industry level (see Column 4 of Table 4). See Table 5 for sample restrictions and further variable definitions. All regressions contain quarter-by-year 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:* CONOCER, ENOE, Mexican Census 2000 (10.6% sample), and U.S. Census 2000 (5% sample).

Online Appendices: Not for Publication

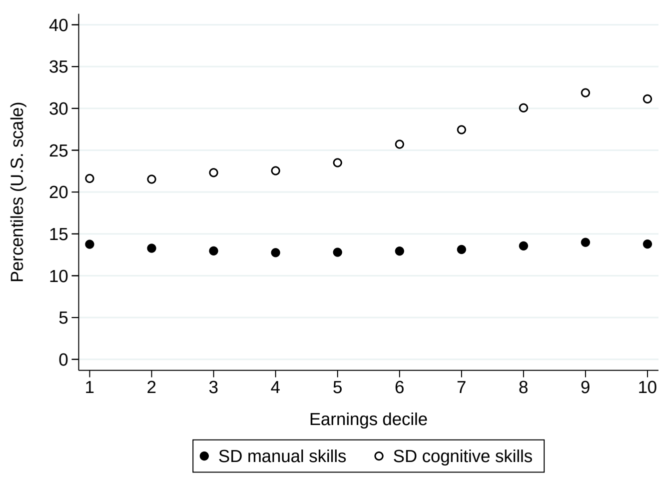
A Further Results

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

(a) Years-of-Schooling Distribution



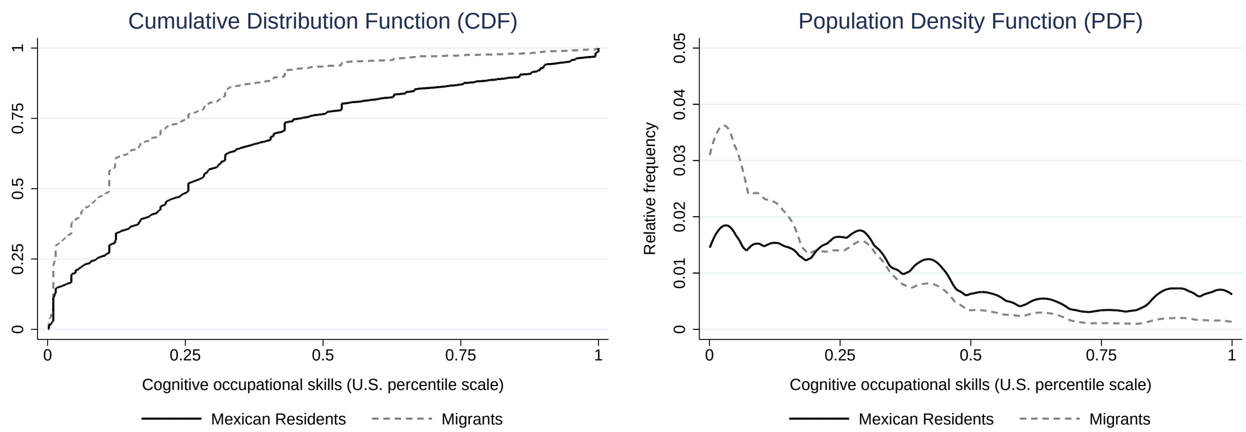
(b) Earnings Distribution



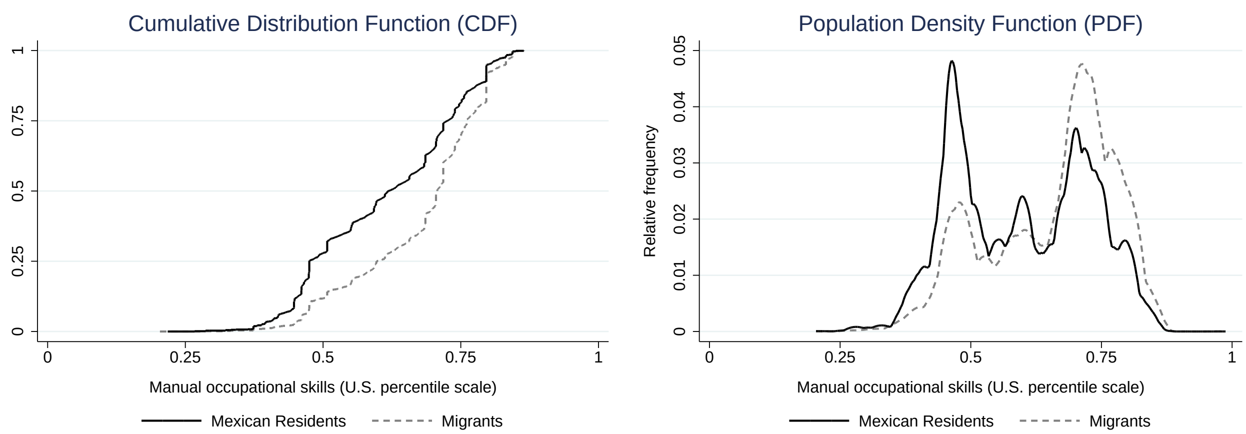
Notes: Figure plots the standard deviations of cognitive skills and manual skills (each expressed as percentile ranks in the U.S. skill distribution) within each year-of-schooling category (Figure A1(a)) and within each earnings decile (Figure A1(b)). Observations are weighted by sampling weights in the Mexican Census 2010. 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 Mexican Census 2000 (not shown). *Data sources:* CONOCER and Mexican Census 2010.

Figure A2: 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 population density functions (right panels) of cognitive occupational skills (Figure A2(a)) and manual occupational skills (Figure A2(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:* CONOCER and ENET.

Table A1: Descriptive Statistics on Migrant Selection

	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	

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*. 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: Functional Form Robustness Results

Dependent variable: migration propensity to the U.S.	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline		6th-order polynomial		Decile fixed effects	
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)

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:* CONOCER and ENOE.

Table A3: 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 5 with returns to skills in the United States based on the U.S. ACS 2010. See Table 5 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:* CONOCER, ENOE, Mexican Census 2000 (10.6% sample), and U.S. ACS 2010 (1% sample).

Table A4: 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 5 using ENET and with returns to skills in the United States based on the U.S. ACS 2010. See Table 5 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:* CONOCER, ENET, Mexican Census 2000 (10.6% sample), and U.S. ACS 2010 (1% sample).

B Related Literature

There is an abundant literature dealing with the selection of international migrants (see Table B1). Three observations stand out. First, ever since Borjas (1987), this field of research has expanded rapidly. Second, the large majority of studies use either an individual's educational attainment or some measure of individual earnings as proxies for 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.

Table B1: Literature on the Selection of Migrants

Paper	Skill measure	Migration flow	Consistent with Roy/Borjas model
Borjas (1987)	entry earnings in destination (U.S.)	Many → U.S.	partly
Ramos (1992)	predicted earnings	Puerto Rico → U.S.	yes
Zavodny (2003)	percent skilled	51 countries → U.S.	no
Feliciano (2005)	education	32 countries → U.S.	no
Borjas (2008)	education	Puerto Rico → U.S.	partly
Grogger and Hanson (2011)	education	Cross country	no
Abramitzky et al. (2012)	father's occupation	Norway → U.S.	yes
	own occupation		partly
Belot and Hatton (2012)	education	80 countries → 29 countries	partly
Stolz and Baten (2012)	age heaping	52 countries → 5 countries	yes
Borjas (2014)	entry earnings in destination (U.S.)	Many → U.S.	yes
Gould and Moav (2016)	education	Israel → U.S.	yes
	residual earnings		partly
Parey et al. (2017)	predicted earnings	Germany → many	yes
Borjas et al. (2017)	earnings in home country	Denmark → many	yes
	residual earnings		yes

Notes: Table shows related papers dealing with migrant selection (partly adopted from Parey et al., 2017).

The literature that specifically deals with Mexican migration to the United States yields similar insights (see Table B2). 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.[47] 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 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 educational selection 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

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

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 B2: 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 Constructing Comparable Measures of Skills

CONOCER and O*NET both measure the job content in respective populations, but they differ in organization, degree of detail, and emphasis on specific domains, which means that not all questions are of a similar nature in the two surveys. However, despite the differences in design, each question domain in CONOCER can be mapped to one or two similar domains in O*NET, the exception being areas of responsibility, which we do not use (see Table C1). To prevent any inconsistency that could arise from merging questions from conceptually different O*NET domains, mapping in such cases is restricted to the domain with most matching questions.

Table C1: Mapping of CONOCER Domains to O*NET Domains.

CONOCER domain	O*NET domain	Missing data
responsibility	—	
knowledge	knowledge	low skilled
use of tools	work activities	
abilities	skills or abilities	low skilled
social skills	work styles	
traits	work styles	
skills	tasks or knowledge	high skilled
physical abilities	abilities	

One limitation in the CONOCER survey is that questions on some domains were given only to high-skilled workers, while others were given only to low-skilled workers (see third column in Table C1). Therefore, it is not possible to use all questions that, in principle, could be mapped when constructing the occupational skills measures. We had to drop the domains of *knowledge*, *abilities*, and *skills* altogether because of systematically missing values for a large fraction of population. This is why we restrict the data to the questions on *use of tools* and *office equipment*, *social skills*, *traits*, and *physical abilities* in CONOCER and, correspondingly, to *work activities*, *work styles*, and *abilities* in O*NET. Reassuringly, however, our measure of Mexicans' cognitive skills is highly correlated with the measure derived from the set of variables on cognitive abilities in CONOCER ($r = 0.71$ for the sample of high-skilled jobs), so the information loss due to the omission of some CONOCER domains is arguably limited.

We also use only the subset of all questions in every domain that is comparable in CONOCER and O*NET. Again, our measures retain much of the original information about the jobs because they are strongly correlated with similarly constructed variables on the full set of questions (with a correlation in the range 0.85–0.97). When restricting the data so as to have a comparable set of questions, the negative correlation of cognitive and manual scores that appears when using the full set of questions is slightly stronger in O*NET (from -0.51 up to -0.59) and somewhat weaker in CONOCER (from -0.47 down to -0.24), but is still preserved.

Table C2 contains all questions selected from both surveys organized into five groups. Column 1 shows the variable from the CONOCER survey. Column 2 shows the corresponding loadings of the first principal component from the decomposition of the respective group of variables (see main text for details). All loadings have the same sign and are normalized to be positive. Column 3 contains the closest equivalent question from O*NET; because some questions in CONOCER are more detailed than the corresponding questions in O*NET, some CONOCER variables are matched to the same O*NET variable. Column 4 shows the loadings of O*NET variables. Reassuringly, we find that all loadings belonging to the same group have the same sign and are usually numerically close to their counterpart in the other survey. This suggests that the domains in both surveys measure similar skill dimensions. Hence there is a high degree of external validity of our measures of skills, even though they are based on different populations. Moreover, the measures are characterized by a high degree of reliability: all variable groups have a Cronbach's α in the range of $0.79-0.96$ (the only exception is CONOCER's *use of tools*, whose Cronbach's α is still reasonably high at 0.69).

As is apparent from Table C2, our measure of cognitive skills is based on several questions that are also related to social skills and personality traits (or, more generally, non-cognitive skills). However, we strongly believe that our measure captures the cognitive rather than the interpersonal dimension. First, there is much overlap between measured cognitive and interpersonal skills in O*NET ($\rho = 0.6$).[48] Second, we examined the correlations of our measure in the O*NET survey and found a stronger relation with cognitive skills than with interpersonal skills. Thus, interpersonal skills are likely to constitute the residual variance of our measure and are not a part of the scores of the principal component which we associate with the cognitive dimension.

[48]We calculate this correlation in O*NET because there is no interpersonal dimension in CONOCER.

Table C2: Correspondence between CONOCER and O*NET Variables

CONOCER		O*NET	
Variable	Rotation	Variable	Rotation
Use of tools			
Electric tools	0.71	Repairing and maintaining electronic equipment	0.38
Agricultural machinery	0.20	Operating vehicles, mechanized devices, or equipment	0.66
Industrial machinery	0.44	Operating vehicles, mechanized devices, or equipment	—
Automated industrial machinery (robots)	0.35	Controlling machines and processes	0.65
Transportation equipment or machinery (vehicles)	0.37	Operating vehicles, mechanized devices, or equipment	—
Physical skills			
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
Creativity	0.28	Innovation	0.35
Self-control	0.35	Self-control	0.22
Independence	0.31	Independence	0.25
Flexibility	0.29	Adaptability/Flexibility	—
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
Use of office equipment			
Office equipment	0.78	Interacting with computers	1.00
Software	0.63	Interacting with computers	—

D Data Details

A Further Datasets to Identify Mexican Emigrants

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.[49] 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 $t + 1$.[50] 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). Extensive information on workers' occupational histories also provides the opportunity to investigate path dependencies of occupational choices and their implications for migrant selection. The MMP further includes information about whether migrants to the United States returned to Mexico and whether they left again for the United States. This allows us to investigate whether the pattern of selection on occupational skills is different for people with several Mexico-U.S. migration episodes.

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

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

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 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, more importantly, 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.

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 frames, migration rates vary substantially across datasets, from 0.3% (per quarter) in ENOE to 2.5% (per year) in the MxFLS. 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).[51]

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

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)	0.0033	–	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:* CONOCER, ENET, ENOE, MMP, and MxFLS.

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 four pre-migration quarters 53% 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).[52] 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.

[52]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, 2017).

Table D2: Range of Occupational Skills in Main SINCO Categories

Occupations	Range		Share
	Cognitive	Manual	
1–digit level			
Officials, directors, and chiefs	0.718	0.420	0.045
Professionals and technicians	0.877	0.583	0.145
Auxiliary workers in administrative activities	0.742	0.453	0.044
Traders, sales clerks, and sales agents	0.579	0.180	0.099
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	0.132
Operators of industrial machinery, assemblers, and drivers	0.733	0.397	0.129
Workers in elementary and supportive activities	0.353	0.507	0.179
Average	0.663	0.476	
2–digit level			
Average	0.431	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:* CONOCER and ENOE.

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:

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

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

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

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

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

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:

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

F Returns to Occupational Skills

The model specified in Section III.A predicts that the main drivers of 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). For Mexican residents, we use data from the 2000 Mexican Census taken from the Integrated Public Use Microdata Series (IPUMS) International database (Minnesota Population Center, 2015, Mexican National Institute of Statistics, Geography, and Informatics). For recent Mexican migrants, we draw on data from the 2000 U.S. Census and the 2010 U.S. American Community Survey (ACS) taken from the IPUMS USA database (Ruggles et al., 2015).[53]

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 specific skills in a Mincer-type framework (e.g., Autor and Handel, 2013; Hanushek et al., 2015), holding constant the other skill level. In particular, 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.

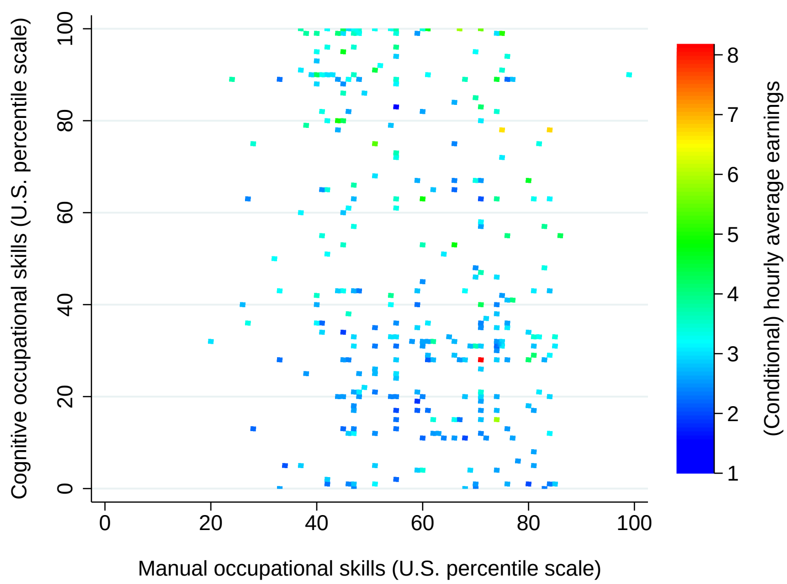
We begin by providing visual evidence on the distribution of hourly earnings (conditional on control variables) by skill percentiles for Mexicans in the Mexican Census 2000 (Figure F1(a)) and for the recent Mexican migrants in the U.S. Census 2000 (Figure F1(b)). The figures aid our understanding of 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

[53] Samples contain males aged between 16 and 65 who are not currently enrolled in school. We restrict samples to those who have reported working between 20 and 84 hours per week and drop the top and bottom 0.5% of the data. For the 2000 Mexico Census, samples are further restricted to individuals born in Mexico. Hourly earnings are constructed by dividing reported monthly earnings by 4.5 times hours worked per week (see also Chiquiar and Hanson, 2005; Fernández-Huertas Moraga, 2011). Hourly earnings in the 2000 U.S. Census and the 2010 ACS are constructed by dividing reported yearly earnings by the number of reported weeks worked per year (using the respective mean of the reported intervals of the number of weeks) times hours worked per week.

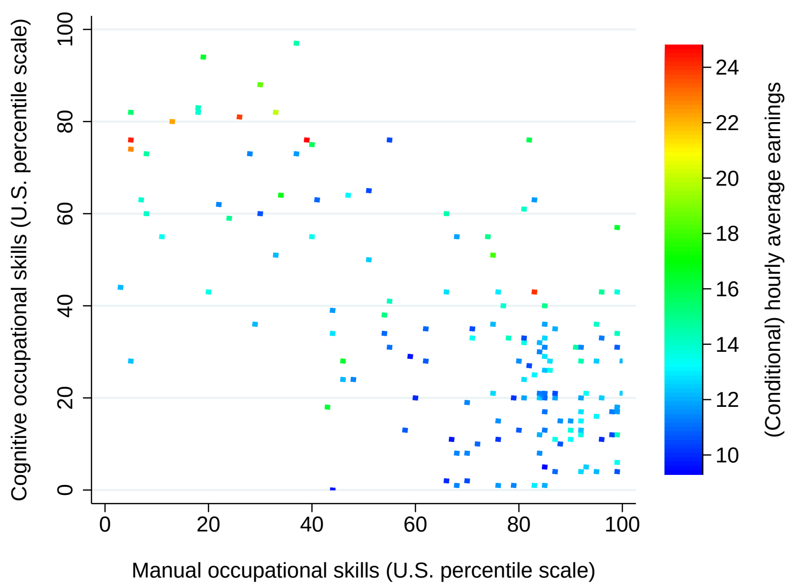
power parities) is higher in the United States than in Mexico. Second, most Mexican workers in the United States cluster in high-manual, low-cognitive occupations. Interestingly, most of them work in occupations that require manual skills above the 80th percentile of manual skills—a percentile that does 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:* CONOCER, Mexican Census 2000 (Figure F1(a)), and U.S. Census 2000 (Figure F1(b)).

Tables F1 and F2 show the results of the earnings regressions. 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 extremely 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).[54] 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).[55] 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.[56]

For comparison, Columns 4–6 of Table F2 provide return estimates based on the ACS 2010 instead of the U.S. Census 2000. 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.

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). For Mexicans who migrated before 1990, we find that returns increase with time spent in the United States, possibly due to integration or skill upgrading (following a potential skill downgrading, as documented in Dustmann et al., 2013, 2016). However, the opposite is true when also considering Mexican migrants to the United States up to the year 2000. In both cases, however, returns to occupational skills are quite similar to those of recent Mexican migrants. 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).

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

[55]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.

[56]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.

Table F1: Returns to Occupational Skills in Mexico

Dependent variable: log hourly earnings			
	(1)	(2)	(3)
	Linear	Decile fixed effects	
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:* CONOCER and Mexican Census 2000 (10.6% sample).

Table F2: Returns to Occupational Skills in the United States

Dependent variable: log hourly earnings						
	(1)	(2)	(3)	(4)	(5)	(6)
	U.S. Census 2000			ACS 2010		
	Linear	Decile fixed effects		Linear	Decile fixed effects	
Panel A: Recent Mexican migrants						
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						
Manual skills	0.230***	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						
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						
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 × 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:* CONOCER, U.S. Census 2000 (5% sample) and U.S. ACS 2010 (1% sample).

G Robustness of the Results on Emigrant Selection on Occupational Skills

The goal of this section is to explore the robustness of our main results on emigrant selection on occupational skills. We also investigate the persistence of selection on occupational skills.

A *Robustness across Datasets and Specifications*

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 G1 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. The pattern is also 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 (see also Subsection C). 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.

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

Dependent variable: migration propensity to the U.S.							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					First occ	Last occ	Within state
Cognitive skills	–0.097***	–0.132***		–0.128***	–0.136***	–0.135***	–0.147***
	(0.010)	(0.013)		(0.015)	(0.015)	(0.013)	(0.015)
Manual skills	0.069***	0.057***		0.087***	0.070***	0.102***	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 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. 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:* CONOCER and MMP.

Tables G2 and G3 show the analogous results using data from ENET and MxFLS, respectively. Results indicate 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.

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

Dependent variable: migration propensity to the U.S.							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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. 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:* CONOCER and ENET.

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

Dependent variable: migration propensity to the U.S.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					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)
State-of-living 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. 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:* CONOCER and MxFLS.

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 education (and age). 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 yielding marginal effects very similar to those from the linear probability model.

B Migration Status and Temporary Migration

According to the latest estimate from Pew Research Center, about half of Mexican emigration is unauthorized, meaning illegal or undocumented (Gonzalez-Barrera and Krogstad, 2017). Because unauthorized migrants are overrepresented in manual-intensive occupations,[57] the question arises to what extent the pattern of selection on occupational skills differs by migration status. The MMP data allow us to investigate this issue. In the data, 27% of migrants have a legal migration status. The remaining sample consists of unauthorized migrants and of those who did not know or refused to report their migration status. Estimating the selection on occupational skills for both migrant groups shows a qualitatively similar pattern: there is positive selection on manual skills and negative selection on cognitive skills (Columns 1 and 2 of Table G4). However, the degree of selection is more pronounced for migrants with no or unknown legal status. This result is consistent with the observation that unauthorized migrants are often employed in manual-intensive occupations.

Furthermore, much of the Mexican migration is temporary in nature, and many Mexicans migrate to the United States multiple times. Both is unlikely to affect our results much. First, dropping migrants with a temporary U.S. contract (i.e., Bracero or H-2A visa) and 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 3 of Table G4). The same is true when we drop return migrants (Column 4). Second, using ENOE, we can show that results are robust to dropping agricultural workers (Figure G1), who are most likely to migrate for seasonal and temporary work (e.g., by making use of the H-2A visa program).[58] 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 G2).

[57] Pew Research Center estimates suggest that, in the year 2014, the share of unauthorized migrants in the U.S. workforce was 26% in farming and 15% in construction (compared to a share of 5% in the civilian workforce overall). While these numbers refer to the total population of unauthorized immigrants, Mexicans are by far the most prevalent among them (52% in 2014). See Krogstad et al. (2017) for details.

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

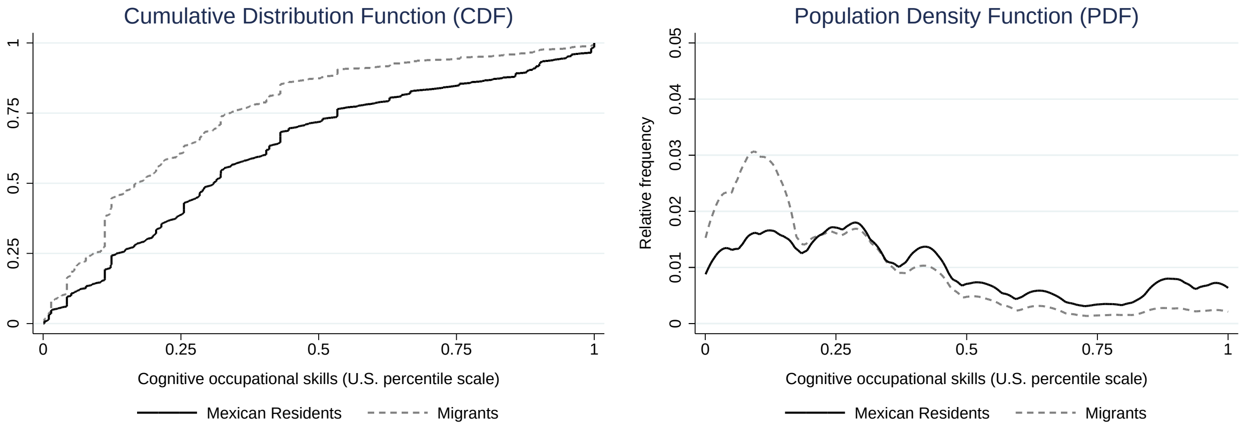
Table G4: Emigrant Selection on Occupational Skills: Migration Status and Temporary Migration

Dependent variable: migration propensity to the U.S.				
	(1)	(2)	(3)	(4)
	Legal status		Permanent migrants	
	Known	Unknown	No temporary contracts or work permits	No return migrants
Cognitive skills	–0.040***	–0.090***	–0.109***	–0.123***
	(0.007)	(0.013)	(0.014)	(0.017)
Manual skills	0.025***	0.064***	0.059***	0.056**
	(0.010)	(0.018)	(0.020)	(0.024)
Cognitive skills × manual skills	–0.010***	–0.021***	–0.022***	–0.032***
	(0.003)	(0.004)	(0.005)	(0.006)
Years of schooling	0.010***	–0.027***	–0.017***	–0.014*
	(0.003)	(0.006)	(0.006)	(0.007)
Age	–0.003***	–0.041***	–0.041***	–0.061***
	(0.001)	(0.002)	(0.002)	(0.002)
Observations	463,435	468,347	469,419	385,287

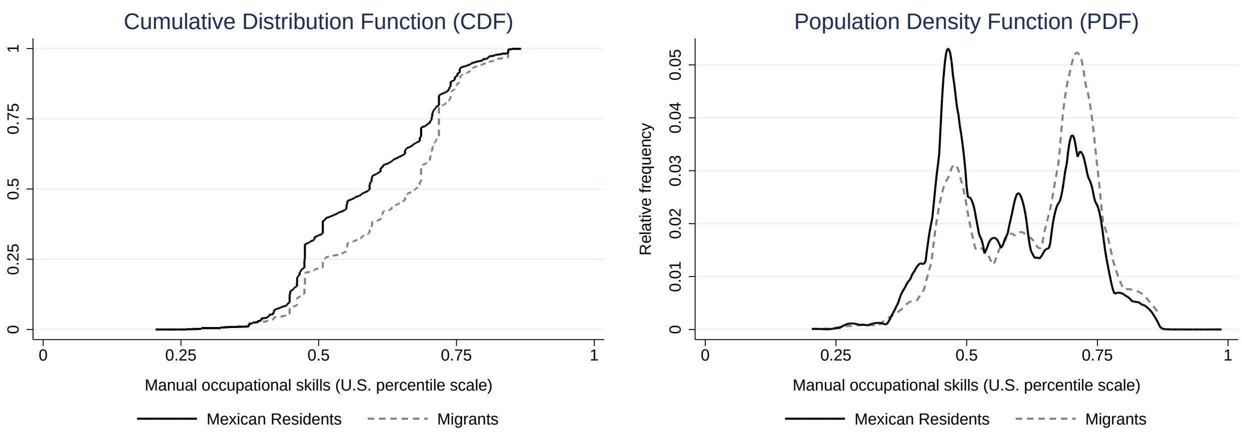
Notes: Table presents baseline results for different subsamples. In Column 1, sample of Mexican migrants includes only persons who migrate to the United States with official U.S. documentation (i.e., legal residence permit, contracts (Bracero program or H2A visa), and temporary work permits); 26.53% 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. In Column 3, we drop migrants with a temporary U.S. contract (Bracero program or H2A visa) or work permit (16.28% of migrant sample). In Column 4, we drop all observations after the first move to the United States, that is, estimation is without return migrants. 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 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:* CONOCER and MMP.

Figure G1: Emigrant Selection on Occupational Skills: Omitting Agricultural Workers

(a) Cognitive Occupational Skills

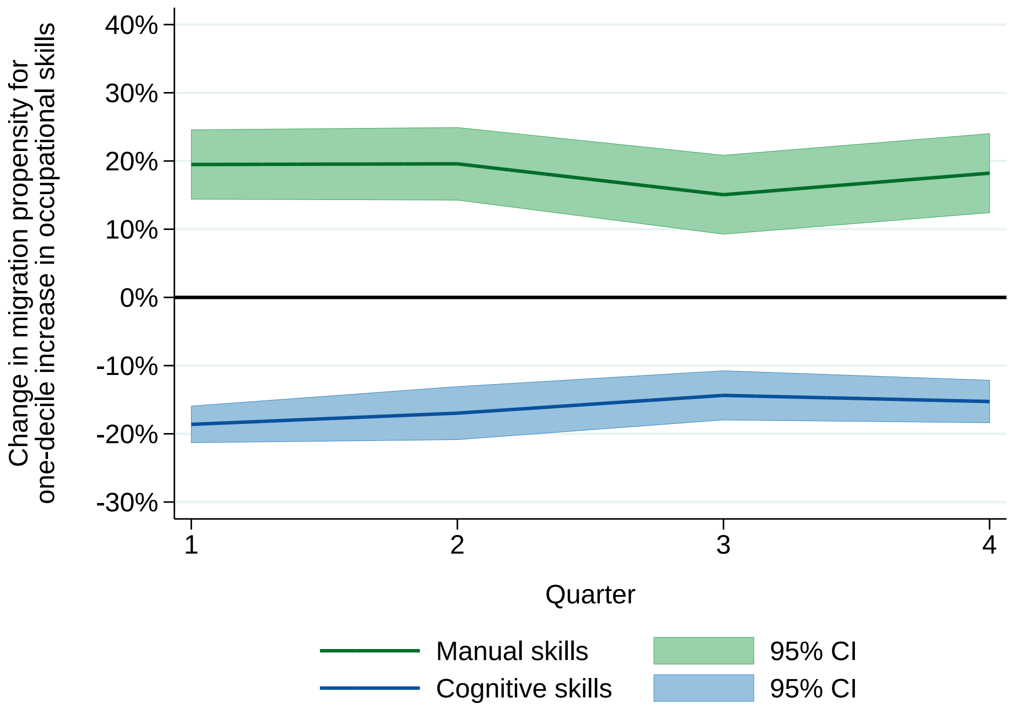


(b) Manual Occupational Skills



Notes: Figures show cumulative distribution functions (left panels) and population density functions (right panels) of cognitive occupational skills (Figure G1(a)) and manual occupational skills (Figure G1(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:* CONOCER and ENOE.

Figure G2: Emigrant Selection by Quarter

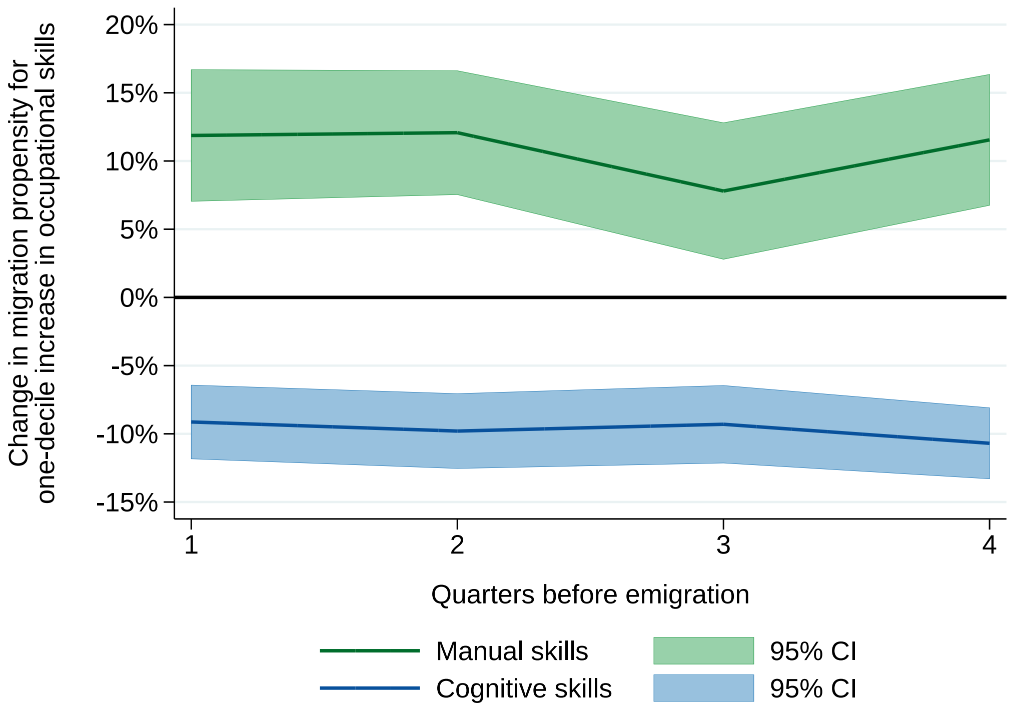


Notes: Graph shows selection on cognitive and manual skills (based on the specification in Column 3 of Table 2) when data are grouped by quarter. *Data sources:* CONOCER and ENOE.

C Skill-Specific Labor-Market Shocks

One potential concern is 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. To check whether negative labor-market shocks shortly before migration may explain the pattern of negative selection on cognitive skills and positive selection on manual skills, we investigate occupational changes during the four quarters preceding the migration move. Figure G3 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. Thus, imperfect job matches due to skill-specific labor-market shocks are unlikely to affect our results.

Figure G3: 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 3 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:* CONOCER and ENOE.

There is also reason to suspect that skill mismatch 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 G5 and G6).

Table G5: Emigrant Selection on Occupational Skills: Occupational Tenure and Age Restrictions (MMP)

Dependent variable: migration propensity to the U.S.							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Occupational tenure			Age			
	> 3 years	> 5 years	> 10 years	> 20 years	> 25 years	> 30 years	> 35 years
Cognitive skills	–0.124***	–0.114***	–0.101***	–0.127***	–0.103***	–0.090***	–0.070***
	(0.013)	(0.012)	(0.011)	(0.015)	(0.014)	(0.015)	(0.016)
Manual skills	0.103***	0.107***	0.091***	0.089***	0.098***	0.095***	0.111***
	(0.018)	(0.017)	(0.015)	(0.022)	(0.020)	(0.021)	(0.022)
Cognitive skills × manual skills	–0.038***	–0.038***	–0.036***	–0.032***	–0.028***	–0.027***	–0.029***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Years of schooling	–0.019***	–0.020***	–0.017***	–0.018***	–0.022***	–0.023***	–0.022***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Age	–0.031***	–0.025***	–0.018***	–0.045***	–0.039***	–0.038***	–0.033***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	454,945	438,168	388,183	409,662	338,859	268,215	203,660

Notes: Sample includes Mexican males up to age 65 who meet the occupational tenure or age restriction specified in the column header. 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 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:* CONOCER and MMP.

Table G6: Emigrant Selection on Occupational Skills: Age Restrictions (ENOE)

Dependent variable: migration propensity to the U.S.					
	(1)	(2)	(3)	(4)	(5)
	Baseline	> 20 years	> 25 years	> 30 years	> 35 years
Cognitive skills	–0.164***	–0.152***	–0.134***	–0.121***	–0.108***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Manual skills	0.182***	0.175***	0.150***	0.128***	0.121***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)
Cognitive skills × manual skills	–0.079***	–0.074***	–0.060***	–0.050***	–0.045***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Years of schooling	0.010*	0.006	0.001	–0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age	–0.032***	–0.034***	–0.033***	–0.030***	–0.032***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2,959,528	2,631,229	2,241,222	1,869,897	1,513,343

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 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:* CONOCER and ENOE.

However, employment shocks might also have a long-lasting effect on occupational choices, that is, individuals being forced by a labor-market shock to move to a worse occupation may have problems to make the reverse switch later in the career.[59] 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. The first occupation is likely not affected by labor-market shocks and plausibly orthogonal to migration decisions later in life. Moreover, plenty of evidence suggests that occupational careers are affected by early job choices.[60] 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 (G1)), 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 (G2)):

$$\text{(G1)} \qquad \text{migprop}_{it} = \alpha_0 + \alpha_1 \widehat{z_{c,it}^{current}} + \alpha_2 \widehat{z_{m,it}^{current}} + \alpha_3 \widehat{z_{c,it}^{current} \times z_{m,it}^{current}} + \mathbf{X_{it}^{'}}\gamma + \zeta_t + \epsilon_{it}$$

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:

$$\text{(G2)} \qquad k = \pi_0 + \pi_1 z_{c,it}^{first} + \pi_2 z_{m,it}^{first} + \pi_3 z_{c,it}^{first} \times z_{m,it}^{first} + \mathbf{X_{it}^{'}}\delta + \zeta_t + \nu_{i,t}$$

Table G7 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.[61]

In light of this evidence, we consider it highly unlikely that skill-specific employment shocks

[59]Nedelkoska et al. (2017) find that German workers frequently switch to less demanding jobs after plant shutdown and that a considerable share of these moves is persistent.

[60]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.

[61]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.

prior to migration are responsible for our results.

Table G7: Path Dependency in Skill Accumulation: Results from 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:* CONOCER and MMP.

D 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.

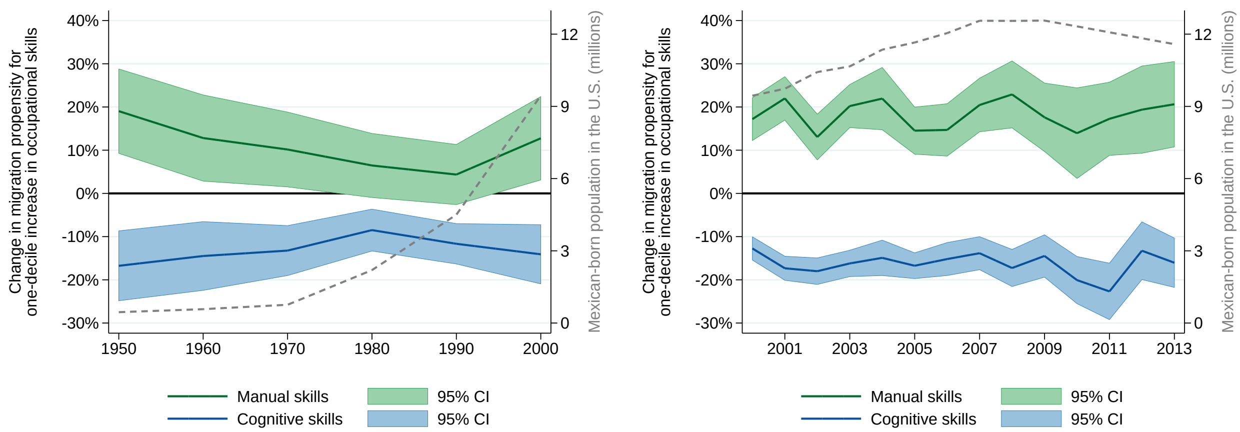
Pooling data from ENET and ENOE, the right panel of Figure G4 plots the annual migration propensity for a one-decile increase in cognitive (blue line) and manual (green line) occupational skills in the period 2000–2013.[62] Remarkably, we observe that Mexican emigrants have been positively selected on manual skills and negatively selected on cognitive skills over the entire period. Notably, this pattern also holds during the recent decline in Mexican emigration.

While there has already been a large Mexican community in the United States in the beginning of the 2000's, one might wonder whether the selection pattern changes when considering earlier periods. The left panel of Figure G4 shows that even though the Mexican migrant community in the United States in the 1950s, 1960s, and most of the 1970s was very small, the pattern of selection of Mexican emigrants on occupational skills is 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.[63]

[62] Estimates are based on the model in Column 3 of Table 2.

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

Figure G4: 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:* CONOCER, MMP (left figure), and ENET/ENOE (right figure).

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 papers—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).

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 5 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 5 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:* CONOCER, ENOE, Mexican Census 2000 (10.6% sample), and U.S. Census 2000 (5% sample).

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 Table H2). And third, we are mostly interested in the *relative* contribution of basic versus occupational return measures 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Recent Mexican migrants		All Mexican migrants		Spanish-speaking migrants from Central/South America		U.S.-born with Mexican ethnicity	
Panel A: Mean selection on earnings								
Dependent variable: migration propensity to the U.S.								
Log hourly earnings	–0.170***	–0.038	–0.224***	–0.083***	–0.221***	–0.102***	–0.265***	–0.136***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)	(0.031)
Δ basic returns$^{US,2000}_{MEX,2000}$	0.719***	0.246***	0.523***	0.048	0.634***	0.271***	0.438***	0.034
	(0.056)	(0.061)	(0.058)	(0.062)	(0.069)	(0.072)	(0.073)	(0.075)
Δ occupational returns$^{US,2000}_{MEX,2000}$		1.493***		1.577***		1.364***		1.338***
		(0.099)		(0.102)		(0.105)		(0.092)
Panel B: Selection along the earnings distribution								
Dependent variable: migration propensity to the U.S.								
2nd quintile	–0.002	0.053	–0.012	0.041	–0.008	0.045	–0.018	0.028
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
3rd quintile	–0.209***	–0.111	–0.233***	–0.131*	–0.228***	–0.129*	–0.248***	–0.156**
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.069)	(0.068)	(0.069)
4th quintile	–0.350***	–0.192***	–0.400***	–0.229***	–0.393***	–0.239***	–0.432***	–0.277***
	(0.065)	(0.066)	(0.065)	(0.066)	(0.065)	(0.066)	(0.066)	(0.066)
5th quintile	–0.383***	–0.139**	–0.494***	–0.234***	–0.489***	–0.271***	–0.578***	–0.339***
	(0.066)	(0.068)	(0.067)	(0.068)	(0.067)	(0.069)	(0.066)	(0.067)
Δ basic returns$^{US,2000}_{MEX,2000}$	0.688***	0.215***	0.497***	0.020	0.602***	0.233***	0.417***	0.005
	(0.056)	(0.061)	(0.058)	(0.063)	(0.069)	(0.072)	(0.072)	(0.075)
Δ occupational returns$^{US,2000}_{MEX,2000}$		1.457***		1.539***		1.327***		1.308***
		(0.098)		(0.101)		(0.105)		(0.091)

Notes: Table shows specifications analogous to those in Columns 2 and 4 of Table 5 with returns to skills in the United States calculated based on different population groups. In Columns 1 and 2 (baseline), U.S. returns are constructed for recent Mexican migrants in the U.S. (immigrated 10 years prior to the survey with an age of 16 years or more at time of arrival). In Columns 3 and 4, U.S. returns are constructed for all Mexican migrants in the United States. In Columns 5 and 6, U.S. returns are constructed for Spanish speaking migrants from Central and South America (excluding Mexico), and in Column 7 and 8, U.S. returns are constructed for U.S. born natives with Mexican ethnicity. See Table 5 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:* CONOCER, ENOE, Mexican Census 2000 (10.6% sample), and U.S. Census 2000 (5% sample).

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).[64]

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

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 5 using ENET data. See Table 5 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:* CONOCER, ENET, Mexican Census 2000 (10.6% sample), and U.S. Census 2000 (5% sample).

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 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 5 using average earnings, constructed as simple average of log hourly earnings in pre-migration quarters. See Table 5 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:* CONOCER, ENET, Mexican Census 2000 (10.6% sample), and U.S. Census 2000 (5% sample).

Online Appendix References

Abraham, K. G. and Farber, H. S. (1987). Job Duration, Seniority, and Earnings. *American Economic Review*, 77(3):278–297.

Abramitzky, R., Boustan, L. P., and Eriksson, K. (2012). Europe's Tired, Poor, Huddled Masses: Self-Selection and Economic Outcomes in the Age of Mass Migration. *American Economic Review*, 102(5):1832–1856.

Acemoglu, D. and Autor, D. H. (2011). Skills, Tasks, and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D. E., editors, *Handbook of Labor Economics Volume 4*, volume 4B. Amsterdam: Elsevier.

Ambrosini, J. W. and Peri, G. (2012). The Determinants and the Selection of Mexico-US Migrants. *World Economy*, 35(2):111–151.

Autor, D. and Handel, M. (2013). Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics*, 31(2):S59–S96.

Belot, M. V. K. and Hatton, T. J. (2012). Immigrant Selection in the OECD. *Scandinavian Journal of Economics*, 114(4):1105–1128.

Borjas, G. J. (1987). Self-Selection and the Earnings of Immigrants. *American Economic Review*, 77(4):531–553.

Borjas, G. J. (2008). Labor Outflows and Labor Inflows in Puerto Rico. *Journal of Human Capital*, 2(1):32–68.

Borjas, G. J. (2014). *Immigration Economics*. Harvard University Press.

Borjas, G. J., Kauppinen, I., and Poutvaara, P. (2017). Self-Selection of Emigrants: Theory and Evidence on Stochastic Dominance in Observable and Unobservable Characteristics. *Economic Journal*, forthcoming.

Chiquiar, D. and Hanson, G. H. (2005). International Migration, Self-Selection, and the Distribution of Wages: Evidence from Mexico and the United States. *Journal of Political Economy*, 113(2):239–281.

Dustmann, C., Frattini, T., and Preston, I. P. (2013). The Effect of Immigration Along the Distribution of Wages. *Review of Economic Studies*, 80(1):145–173.

Dustmann, C., Schönberg, U., and Stuhler, J. (2016). The Impact of Immigration: Why Do Studies Reach Such Different Results? *Journal of Economic Perspectives*, 30(4):31–56.

Farber, H. S. (1994). The Analysis of Interfirm Worker Mobility. *Journal of Labor Economics*, 12(4):554–593.

Feliciano, C. (2005). Educational Selectivity in U.S. Immigration: How Do Immigrants Compare to Those Left Behind? *Demography*, 42(1):131–152.

Feliciano, C. (2008). Gendered Selectivity: U.S. Mexican Immigrants and Mexican Nonmigrants, 1960-2000. *Latin American Research Review*, 43(1):139–160.

Fernández-Huertas Moraga, J. (2011). New Evidence on Emigrant Selection. *Review of Economics and Statistics*, 93(1):72–96.

Fernández-Huertas Moraga, J. (2013). Understanding Different Migrant Selection Patterns in Rural and Urban Mexico. *Journal of Development Economics*, 103(1):182–201.

Gathmann, C. and Schönberg, U. (2010). How General is Human Capital? A Task-Based Approach. *Journal of Labor Economics*, 28:1–50.

Gonzalez-Barrera, A. and Krogstad, J. M. (2017). What We Know about Illegal Immigration from Mexico. `http://www.pewresearch.org/fact-tank/2017/03/02/what-we-know-about-illegal-immigration-from-mexico/`. Date accessed: 09/26/2017.

Gould, E. D. and Moav, O. (2016). Does High Inequality Attract High Skilled Immigrants? *Economic Journal*, 126(593):1055–1091.

Grogger, J. and Hanson, G. H. (2011). Income Maximization and the Selection and Sorting of International Migrants. *Journal of Development Economics*, 95(1):42–57.

Hanson, G. H. (2006). Illegal Migration from Mexico to the United States. *Journal of Economic Literature*, 44(4):869–924.

Hanson, G. H. and McIntosh, C. (2010). The Great Mexican Emigration. *Review of Economics and Statistics*, 92(4):798–810.

Hanushek, E. A., Schwerdt, G., Wiederhold, S., and Woessmann, L. (2015). Returns to Skills Around the World: Evidence from PIAAC. *European Economic Review*, 73(C):103–130.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47(1):153–161.

Heckman, J. J. and Scheinkman, J. (1987). The Importance of Bundling in a Gorman-Lancaster Model of Earnings. *Review of Economic Studies*, 54(2):243–255.

Ibarraran, P. and Lubotsky, D. (2007). Mexican Immigration and Self-Selection: New Evidence from the 2000 Mexican Census. In Borjas, G. J., editor, *Mexican Immigration to the United States*, chapter 5, pages 159–192. Chicago, IL: University of Chicago Press.

INEGI (2011a). Sistema Nacional de Clasificación de Ocupaciones (SINCO). `http://www.inegi.org.mx/est/contenidos/proyectos/aspectosmetodologicos/clasificadoresycatalogos/sinco.aspx`.

INEGI (2011b). Sistema Nacional de Clasificación de Ocupaciones (SINCO): Crosswalk Between SINCO and CMO. `http://www.inegi.org.mx/est/contenidos/proyectos/aspectosmetodologicos/clasificadoresycatalogos/doc/sinco_tablas_comparativas.xls`.

Jovanovic, B. (1979). Job Matching and the Theory of Turnover. *Journal of Political Economy*, 87(5):972–990.

Kaestner, R. and Malamud, O. (2014). Self-Selection and International Migration: New Evidence from Mexico. *Review of Economics and Statistics*, 96(1):78–91.

Krogstad, J. M., Passel, J. S., and Cohn, D. (2017). 5 Facts about Illegal Immigration in the U.S. `http://www.pewresearch.org/fact-tank/2017/04/27/5-facts-about-illegal-immigration-in-the-u-s/`. Date accessed: 09/26/2017.

McKenzie, D. and Rapoport, H. (2010). Self-Selection Patterns in Mexico-U.S. Migration: The Role of Migration Networks. *Review of Economics and Statistics*, 92(4):811–821.

Minnesota Population Center (2015). Integrated Public Use Microdata Series, International: Version 6.4 [Machine-readable database]. Minneapolis, MN: University of Minnesota.

Mishra, P. (2007). Emigration and Wages in Source Countries: Evidence from Mexico. *Journal of Development Economics*, 82(1):180–199.

Nedelkoska, L., Neffke, F., and Wiederhold, S. (2017). Skill Mismatch and the Costs of Job Displacement. Mimeo.

Orrenius, P. M. and Zavodny, M. (2005). Self-Selection Among Undocumented Immigrants from Mexico. *Journal of Development Economics*, 78(1):215–240.

Parey, M., Ruhose, J., Waldinger, F., and Netz, N. (2017). The Selection of High-Skilled Emigrants. *Review of Economics and Statistics*, forthcoming.

Peri, G. (2012). The Effect of Immigration on Productivity: Evidence from U.S. States. *Review of Economics and Statistics*, 94(1):348–358.

Peri, G. and Sparber, C. (2009). Task Specialization, Immigration, and Wages. *American Economic Journal: Applied Economics*, 1(3):135–169.

Ramos, F. A. (1992). Outmigration and Return Migration of Puerto Ricans. In Borjas, G. J. and Freeman, R. B., editors, *Immigration and the Workforce: Economic Consequences for the United States and Source Areas*, chapter 2, pages 49–66. Chicago, IL: University of Chicago Press.

Rendall, M. S. and Parker, S. W. (2014). Two Decades of Negative Educational Selectivity of Mexican Migrants to the United States. *Population and Development Review*, 40(3):421–446.

Robinson, C. (2017). Occupational mobility, occupation distance and specific human capital. *Journal of Human Resources*, Forthcoming.

Ruggles, S., Genadek, K., Goeken, R., Grover, J., and Sobeku, M. (2015). Integrated Public Use Microdata Series: Version 6.0 [Machine-readable database]. Minneapolis, MN: University of Minnesota.

Steinmayr, A. (2014). When a Random Sample is Not Random. Bounds on the Effect of Migration on Children Left Behind. Kiel Working Paper No. 1975.

Stolz, Y. and Baten, J. (2012). Brain Drain in the Age of Mass Migration: Does Relative Inequality Explain Migrant Selectivity? *Explorations in Economic History*, 49(2):205–220.

Topel, R. and Ward, M. (1992). Job Mobility and the Careers of Young Men. *Quarterly Journal of Economics*, 107(2):439–479.

Villarreal, A. (2014). Explaining the Decline in Mexico-U.S. Migration: The Effect of the Great Recession. *Demography*, 51(6):2203–2228.

Villarreal, A. (2016). The Education-Occupation Mismatch of International and Internal Migrants in Mexico, 2005-2012. *Demography*, 53(3):865–883.

Zavodny, M. (2003). Determinants of Immigrant Selectivity and Skills. *Research in Labor Economics*, 22:269–289.