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By

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Committee in charge:

Professor Dennis Feehan, Co-chair
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Professor Joshua Goldstein
Professor Claudia Masferrer

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Abstract

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The panorama of Mexican migration changed substantially during the 21$^{st}$ century with decreasing emigration flows, a near-zero net migration rate, and increasing return migration. According to the Mexican Census, between 1995 and 2000, about 1.6 million people left Mexico. However, between 2015 and 2020, about 803,000 people emigrated from Mexico. The current dynamics starkly contrast with the decades of high emigration rates from Mexico during the 20$^{th}$ century. In this dissertation, I study one of the changing components: emigration. Understanding the size and composition of emigration is essential as it has unique implications on the migrants, their communities at their origin, their destinations, and repercussions over generations. Migration research is often complex as there is limited detailed data, and many times, it only pertains to a specific stage of migration. These issues usually prevent researchers from analyzing more detailed determinants of migration or from making claims about a general population. I focus on three important elements in migration research: availability of detailed data, understanding migration as a process, and differences by sex.

In the first chapter, I show that an underused high-quality dataset from Mexico, the *Encuesta Nacional de Ocupación y Empleo* (ENOE), can be used to understand migration in Mexico. The ENOE is the Mexican Labor Force Survey. Although it does not track migration directly, its survey structure allows it to identify migrants (both emigrants and immigrants) along with a rich set of covariates. I validate the ENOE by carefully comparing it to gold-standard data such as the Census and the *Encuesta Nacional de la Dinámica Demográfica* (ENADID), a demographic survey. My results find that immigrants and emigrants from the ENOE match standard data across key demographic characteristics. Moreover, in the aggregate, the ENOE produces migration rates comparable to official demographic estimates. The ENOE may be preferred over other data because it has economic and demographic variables of migrants before they leave or after they enter Mexico. Also, it is a frequent and ongoing panel survey, which allows for timely estimates. This chapter also provides guidelines for the practical use of the ENOE for research on migration. Using the ENOE, in addition to official estimates, can provide researchers with an updated view of migration trends and identify areas of research. Due to its richness, the ENOE is the main data for the next two chapters.

In the second chapter, I collaborate with Rui F. Carvalho to analyze an understudied

stage before emigration: preparing to emigrate. International emigration has been identified as a stepwise process entailing the formation of aspirations to emigrate, making preparations for the move, and eventually realizing those intentions and plans. Extant research has either focused on the aspirational phase or on the actual determinants of emigrant abilities, with less attention paid to the phase of preparing or planning for the move. Using the ENOE, we investigate (i) the relationships between emigration preparations and actual international emigration; (ii) whether preparations to emigrate depend on specific demographic and structural characteristics; and (iii) how preparations may affect employment outcomes. We uncover that preparing to emigrate is a rare event. We also find variations in sociodemographic features related to emigration preparations, which are different from predictors of actual emigration. Further, utilizing event study analysis we examine the relationships among employment behaviors, preparations, and emigration. We find that differences between whether preparations are materialized into emigration or not are associated with changes in income, hours worked, and being employed. Overall, the results provide a better understanding of emigration preparations and how they relate to actual emigration and to employment behaviors.

In the third chapter, I consider how international emigration from Mexico differs in a key demographic trait: sex. The share of female emigrants varies across countries: in many countries, emigration is composed of mostly men, while in others, female emigration is slightly above 50%. Smaller flows of female emigrants indicate more extensive structural conditions that prevent the mobility of women. This immobility is a form of inequality between male and female emigrants. This chapter analyzes differences between male and female Mexican emigrants during the 21$^{st}$ century, and explores how they translate into the share of female emigrants. In doing so, I revisit the question of the feminization of international emigration. Between 2000 and 2020, the share of female emigrants increased from 25% to 33%, as a result of decreasing male emigration with a steady female emigration. Using decomposition analysis, I find that this slight feminization process is due to changes in sex-specific patterns of determinants of emigration. This work adds to the extensive literature on Mexican migration by contrasting recent patterns of female selection into migration rather than focusing on male emigration.

Overall, my dissertation fills these gaps in data and substantive comparisons by providing a rich understanding of the composition of migrants before they leave, and if there is a process of feminization of international emigration in Mexico.

Para mi mamá y papá, quienes me enseñaron el valor del trabajo, el amor a la vida y a la familia.
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# Contents

# Chapter 1

# Validation of the Mexican Labor Force Survey for Migration Research

## 1.1 Introduction

In migration research, the constant tension between breadth, frequency and accuracy of data often prompts researchers to collect their own data. However, existing data may be overlooked. In the context of Mexico, a country with large migrant out-flows and a fundamental route of passage for immigrants to the United States (U.S.) from other countries, timely data is vital to understand the migration phenomenon, policy, and the humane treatment of migrants.

Migration statistics in Mexico have primarily used a combination of high-quality data from decennial censuses, demographic household surveys, and administrative data. On the one hand, surveys tend to have detailed questions, but they often lack the statistical power of census responses, which limits the depth of analysis on migrants. On the other hand, censuses happen every ten years which limits the time-specific analysis. Even when the surveys are tailored to understand migration, they may suffer from important limitations that reduce the confidence of migration estimates.

Instead, some researchers have turned to the *Encuesta Nacional de Ocupación y Empleo* (ENOE), which is the Mexican Labor Force Survey. The issue is that the ENOE was created for employment statistics and does not have a migration module. The skepticism in the ENOE is summarized by Pederzini (2018, p.16): *'One limitation of the use of the ENOE to measure migration is that the objective of its sampling design is to capture occupation and employment in Mexico, therefore it is not representative of the migrant population'*. Earlier work expressed concerns about the disaggregation of migration estimates over time and geography (Paredes & Mera-Ceballos, 2012), and cautioned researchers in using only relative measures of migration (Instituto Nacional de Estadística y Geografía, 2012). However, little has been done to evaluate migration in the ENOE, with the exception of Rendall et al. (2011) who compare return migration to a demographic survey in Mexico. Despite its use in research (Bertoli & Murard, 2020; Delgadillo Aguilar et al., 2017; Pederzini, 2012; Rendall & Parker, 2014; Villarreal & Blanchard, 2013), there is no current evidence that the ENOE contains an accurate portrayal of migration which includes emigration and immigration.

In the spirit of using existing data to understand migration, I evaluate migrant characteristics and trends from the ENOE from 2006 to 2019 against other high-quality and representative sources on migration (Censuses and demographic surveys). Within migration, I focus on comparable categories of emigrants from and immigrants to Mexico. This is possible in the ENOE because of its panel structure where households are surveyed for five consecutive quarters, and because of the available variables. In this evaluation, I begin by comparing demographic composition of migrants across data and find that the migrants in the ENOE are very similar to those in my benchmark data. Next, I compare migration rates from the ENOE to official demographic estimates. The rates are similar in trends but are different in the magnitude depending on the year.

Taken together, the ENOE is a reliable source of information on migration which can expand the frontier on migration research in Mexico, particularly on labor migration, family composition and migration during the life course. The ENOE contains more demographic and economic variables on all migrants than other data, which provides the depth of analysis for newer questions in the discipline. Moreover, the frequency and the continuation of the ENOE is key to detect short-term fluctuations in the composition of migrants, which is not possible with censuses and demographic surveys, and can assist in policy interests. However, researchers should be aware of the limitations and advantages of this data. I provide guidelines for the adequate use of the ENOE, and evaluate concerns about migrants in household surveys (i.e., whole-household migration, and timing of migration). Overall, the results add to the existing work by verifying the external consistency of the ENOE for migration research in emigration and immigration from Mexico. Mexico's role as a receiving and sending country of migrants has changed in the last decades (Giorguli-Saucedo et al., 2016), as such there is a need for up-to-date data that can complement existing gold-standard migration sources.

Before evaluating the data, I summarize the most relevant and used sources for migration data in Mexico in section 1.2. Then, I detail the structure and sampling design of the ENOE in section 1.3. The evaluation of demographic characteristics of migrants is carried out in section 1.4 where I also describe the censuses and demographic surveys used, and the specific migrant definitions. Section 1.5 focuses on evaluating migration rates from the ENOE. The discussion of these results in section 1.6 emphasizes the advantages and limitations of the ENOE, which should be useful for researchers looking for data.

## 1.2 Mexican Migration in Data

Mexico is in the unique position of having high-quality and publicly available data from the *Instituto Nacional de Geografía, Estadística e Informática* (INEGI). The INEGI is an autonomous institution of the Mexican government that fields household surveys and the census, and provides economic, social and administrative data which is accessible by all. In addition to data from INEGI, there are other data that come from collaborations across universities and administrative data. In this section, I focus on migration data obtained in Mexico, but to understand migration causes and processes it is advisable to include information on migrants at their destination (Masferrer & Pederzini, 2015). I will begin with data that is representative of specific groups until I cover nationally representative data.

The Mexican Migration Project (MMP) is perhaps one of the most well-known migration-specific surveys. The MMP came as a collaboration between universities in the United States and in Mexico and has data from 1982 until 2019.[1] Ever since the influential work by Massey and Espinosa (1997), the MMP has been used to study the determinants and changes of Mexican migration, and the impacts on families and numerous outcomes. However, a main issue is that it is not nationally representative since they sample localities with high migration rates (Massey & Zenteno, 2000).

Other data that is not nationally representative are the Surveys on Migration along the Northern and Southern Borders of Mexico (Emif Norte and Emif Sur)[2] which collect data on flows of people at airports and bus stations in cities along the Mexican borders. The Emif surveys ask about migrant characteristics such as reason to migrate, occupational profile, time spent, use of visa or other documents to cross, and reason for returning to Mexico. An issue with the Emif surveys is that they are only representative of the populations sampled: people that cross the border into or out of Mexico in specific points of entry. Finally, administrative data can also be useful to understand individual-level characteristics of migrants, but they do not have a sampling design. For instance, the *Matrículas Consulares de Alta Seguridad* (MCAS) have been used to estimate changes in flows from municipalities in Mexico to U.S. states (Caballero et al., 2018). However, aggregate tabulations by migrant characteristics are made available online by the Ministry of Foreign Affairs. Micro-level data are not publicly available.

Having surveyed data that is not nationally representative, I describe data that is. First, the National Survey on Demographic Dynamics (ENADID)[3] from INEGI has provided nationally representative estimates on internal and international migrant counts since 1992.[4] Unfortunately, the ENADID is only carried out every 4 to 5 years. In addition, although the ENADID contains vital questions on the destination, origin, repeated movements, type of legal status used, and motivation of the migrant, it does not contain more information on occupation or schooling of all migrants. Migration theory suggests that both are relevant data to understand migrant selection. Another survey is the Mexican Family Life Survey (MxFLS)[5] which is a longitudinal household survey with 3 waves (2002, 2005-2006, and 2009-2012). A key feature of the MxFLS is that it tracks down people who might have migrated abroad or internally between survey waves. Unfortunately, the most recent wave is 10 years old.

Finally, the Census is the most representative data on migration. It is carried out every 10 years and the last one was in 2020. Between censuses, there has been a population count in 2005 and an intercensus survey in 2015. However these mid-census data have fewer migration questions than the census (Masferrer & Pederzini, 2015). In the basic census form, which applies to everyone, researchers can obtain information about the population

[1] For more details: https://mmp.opr.princeton.edu

[2] Per their names in Spanish, the *Encuesta sobre Migración en la Frontera Norte de México* (Emif Norte) and the *Encuesta sobre Migración en la Frontera Sur de México* (Emif Sur). For more information, see https://www.colef.mx/emif/

[3] In Spanish, *Encuesta Nacional de la Dinámica Demográfica*

[4] Additional details at: https://www.inegi.org.mx/programas/enadid/1992/

[5] For more details, http://www.ennvih-mxfls.org/english/introduccion.html

living in Mexico, including their residence five years earlier. A longer form with a module on international migration is given to a smaller share of the population (about %10). Because of the national scope, rigorous survey design and size, the census is the most reliable source of information for migration data.

More recently, there have been efforts to re-purpose data from digital traces to understand demographic patterns (Cesare et al., 2018; Kashyap, 2021). In migration, there are now methods to use digital traces and traditional data together to provide migration estimates (Alexander et al., 2022; Fiorio et al., 2021; Rampazzo et al., 2021). For Mexico, Facebook API data yields estimates for recent immigrants that are in line with the 2020 Census (Varona et al., 2024). Another example of digital traces comes from bibliometric data. Using author affiliation from 1996 to 2018, Miranda-González et al. (2020) analyze internal mobility of scholars in Mexico. The use of digital trace data for migration research is a developing and promising area but researchers must be aware of its limitations and data quality.

Depending on the research objective, some data may be preferred over other. The availability of questions may drive the choice. For instance, Chort (2014) and Creighton and Riosmena (2013) use the MxFLS because it asks about aspirations to migrate, which is not asked about elsewhere. In the second chapter of this dissertation, I analyze a related but later step in the migration-decision making process: preparations to migrate, which is a question in the ENOE. Other work has preferred to use the ENADID because information on networks is collected (McKenzie & Rapoport, 2007, 2010). Census research has looked at migrant selection in income (Chiquiar & Hanson, 2005), the association between climate and migration (Riosmena et al., 2018), measuring return migration (Masferrer & Roberts, 2012), and measuring changes over time in net migration (Hanson & McIntosh, 2010), However, it is more common for researchers to use multiple data that can complement each other (Hamilton & Bylander, 2020; Nobles, 2013; Rendall & Parker, 2014). The ENOE is an attractive option to complement existing data. In the next section, I describe the ENOE and the literature that has used this data so far.

## 1.3 A Glimpse into the ENOE

The ENOE's primary purpose is to track employment changes every quarter in Mexico. Some of its primary indicators are unemployment and labor informality rates. However, the ENOE can also track migration and migrants' characteristics. From here onward, I use migration to refer to emigration (out-migrants) and immigration (in-migration). The ENOE is a longitudinal survey that follows a nationally representative sample of households in Mexico over 5 quarters. At any quarter, there is a mix of households at different interviews. At each wave, about a fifth of respondents are replaced as they reach their fifth and last interview by newly sampled households. On average, a quarter contains about 400,000 individual observations. By pooling all observations since the first ENOE survey wave in 2005 until 2020 Q1,[6] I have about 20 million person-quarter observations.

To obtain the nationally representative estimates, the ENOE follows a two-stage stratified

[6]I stop at this quarter because of changes in the survey. At the beginning of the Covid-19 pandemic, the 2020 Q2 wave was conducted by telephone. From July 2020, interviews began to be conducted in person but with a newer format of the ENOE (ENOE$^N$) which contains more questions.

cluster sampling design. The population of interest is all dwellings in Mexico. The sampling frame comes from the National Household Framework (a product from each recent Census). Dwellings are categorized into primary sampling units (PSU) based on location. The PSU are then stratified by 1) social and demographic characteristics of people from the closest Census; and 2) geography (state, urban/rural/periphery, and population size of locality). For each strata, PSUs are randomly selected, then within each PSU, dwellings are drawn. All households within a dwelling are interviewed. This probabilistic sample yields aggregate results that are representative nationally, by states, by large city, and by city sizes (localities with a population i) $> 100,000$, ii) between $< 99,000$ and $> 2,500$ and iii) $< 2,500$). The household weight is then adjusted for non-response and changes in the population projections (Instituto Nacional de Estadística y Geografía, 2007).

The ENOE offers a large range of information on economic traits (employment, occupation, wages, public benefits, and health care), demographic characteristics (sex,[7] age, education, marital status and number of children born), and geographic distribution. To identify migrants, I compare household rosters between survey waves following Instituto Nacional de Estadística y Geografía (2012), Paredes and Mera-Ceballos (2012), and Villarreal (2014). Relative to the roster from the previous quarter, any absent household members are reported by the remaining respondents who also inform on the broad destination and reason for departure. Characteristics of emigrants are obtained from the last wave when they were a resident. Immigrants are identified as "new residents" to the household and their origin and motive for integration to the household is recorded. Therefore, I can observe the timing and characteristics of migrants. A limitation of the ENOE is that destinations are not specific, instead possible answers are: "another country", "another state in Mexico", and "within the same state". I assume that most international emigrants move to the U.S, as the ENADID suggests that over 90% of migrants go to the U.S. Relative to U.S. data, legal status of emigrants is unlikely to affect response rates in the ENOE. ENOE emigrants are likely composed of future documented and undocumented immigrants to the U.S.

The ENOE has been used for different settings to answer questions in economics, health studies, statistics and migration. For migration research, the ENOE has been used to analyze migrant selection, return migration, characteristics of migrants, and internal migration. Within each area, researchers have focused on producing estimates of migrant rates (or counts) or of specific individual characteristics.

The work that looks at migrant selection, questions if Mexican migrants are less or more educated than their non-migrant peers. Results are conflicting since some point to a positive selection (Chiquiar & Hanson, 2005; Villarreal, 2016) while others point to negative selection (Moraga, 2011; Rendall & Parker, 2014). Moraga (2011) uses the ENOE's predecessor, the *Encuesta Nacional de Empleo* (ENE), to study immigrant selection for the 2000 to 2004 period. His results suggest that male migrants are less educated than non-migrant Mexicans. Using a larger range of household surveys that span from 1992 to 2010, Rendall and Parker (2014) find that the negative selection has persisted even though there has been progress in educational attainment over time of the general Mexican population. Interestingly, Rendall and Parker (2014) mix 4 different and nationally representative household surveys conducted in Mexico: ENADID, ENE, ENOE and the MxFLS. Using only the ENOE from 2005 to 2012,

[7]This is sex as reported by the respondent, which may or may not correspond to gender.

Villarreal (2016) adds to the selection discussion by providing evidence that when comparing within an occupation, Mexican migrants are positively selected in terms of education. Lastly, Lowell and Pederzini (2012) calculate sex-composition of migrant flows using the ENOE to understand if there highly-educated migrant flows are feminized.

Other work has used the ENOE to distinguish the consequences of migration in their origin households. Alcaraz et al. (2012) use the ENOE to explore households with ties to migrants rather than migrants themselves. The authors examine if receiving remittances changes children's time allocation between education and labor. Bertoli and Murard (2020) consider the consequences of international migration on household dissolution and formation: remaining household members can join other households or they can receive new members. They find that households that have migrants are more likely to drop out of the sample (than non-migrant households) and this leads to an undercount of migrants, at least for the period 2005-2007.

In some of the first work to use the ENOE for migration research, Rendall et al. (2011) assess the ENOE (from 2005 to 2009) against the ENADID and produce estimates of return migration. Specifically, they find that the ENOE does not undercount these migrants. However, they do not assess whether emigrant or immigrant rates from the ENOE are comparable to other sources. Other work has provided some estimates of emigration rates (Delgadillo Aguilar et al., 2017) and return migrant counts (Mendoza Cota, 2014; Mendoza-Cota, 2012) without a thorough evaluation of the estimates. This evaluation is important because household surveys, similar to the ENOE, that are not created to survey migrants have limitations in the definition of migrants and the ability to correctly identify them (Carletto et al., 2012). Moreover, Hamilton and Savinar (2015) stress that the attrition in panel surveys caused by households where all members migrate is not random, which can lead to an important undercount of migrants from specific demographic groups.

Overall, there is a no unified evaluation of the ENOE. Since the ENOE was not intended for migration research, it is important to assess whether it can adequately portray the migration rates and migrant-related outcomes. Moreover, existing validation exercises focus on a single type of migration (Rendall et al., 2011), but there is no work that assesses in and out migration. This paper can contribute to this gap in the literature and provide practical guidelines for when to use the ENOE.

## 1.4 Comparing Demographic Characteristics

To validate the ENOE, I will rely on two existing and nationally representative data that are widely accepted as gold standards for migration data: the Mexican Census and the demographic survey ENADID. I use data from Mexico, rather than the U.S. because I want to avoid bias from the undercount of specific migrant groups (i.e., undocumented migrants, farm workers in remote dwellings).

In Mexico, the Census is collected every ten years to estimate the size, age structure, gender distribution, and other attributes of the population. A nationally representative subset of households receives an extended questionnaire, which includes questions on whether a member of the household had moved abroad within the last 5 years. As a result, for sampled households, there is a complete list of emigrants that left within the five-year window. This extended questionnaire also captures the sex, age at departure, destination (country), and return status of the migrants.

The ENADID follows a similar structure to the extended Census questionnaire, as it is meant to provide demographic insights between Census years. Again, sampled households are asked to provide a list of emigrants during the last five years and their characteristics. Although the ENADID is fielded on a much smaller sample of households, its estimates are nationally representative. Both the Census and the ENADID ask about place of birth and residence in the past.

The ENOE differs from the ENADID and the Census in three ways. First, emigrants in the ENOE leave in a specific quarter which we observe. Emigrants in the Census left within the last five years and their time of departure is reported by other household members. This distinction is important because the ENOE may suffer from less recall bias than the Census as the emigrant characteristics are recorded directly from the respondent before their departure. Together these differences mean that the ENOE may provide a more accurate count of emigrants within a year than when using the reported (by remaining household members) year of emigration in the Census (or ENADID). Second, all three data cannot report migrants where all household members have migrated. This is an important limitation but I explore solutions for this in appendix A.8. Third, the ENOE does not contain any information on citizenship, length of stay or type of documents used if someone migrated. Even when taking into account these differences, it is still possible to compare measures of migration between the data, which is done in the following sections.

### 1.4.1 Approach

To compare the ENOE to the 2010 and 2020 Census, and three waves of the ENADID (2009, 2014, 2018), I select the ENOE quarters that coincide with the quarter when the Census and the ENADID were carried out. Appendix A.1 maps the exact ENOE quarters used. In terms of preparing the ENOE, I collapse panel observations to the last reported characteristics. For emigrants, this is the immediate period before they leave. For immigrants, characteristics correspond to the last household interview (rather than the conditions at entry). For constant characteristics, choosing the first or last observation should not matter but conditions can change between quarters, I suggest using information closest to the entry or departure of the migrant. This data processing is based on the ENOE manual (Instituto Nacional de Estadística y Geografía, 2007) and Paredes and Mera-Ceballos (2012). To clarify the process, Appendix A.2 explains the steps with a diagram. Next, I compared Census, ENADID, and ENOE questionnaires and found relevant and comparable migration questions across all data. Table 1.1 summarizes the areas where the data are potentially comparable. For the specific survey questions, please refer to Appendix A.3.

Table 1.1 has two panels for immigration to and emigration from Mexico. The two immigrant definitions are immigrant by place of birth and immigrant by place of residence; both include movers from outside or within Mexico to add more layers of comparison. The emigrant definition only concerns international movers from Mexico but is measured over two time intervals (one or five years).

**Table 1.1:** Migration definitions and comparison between ENOE, Census and ENADID for data validation

| Migrant definition | ENOE | Census | ENADID | Categories of analysis for validation |
|---|---|---|---|---|
| | | **Immigrant definitions** | | |
| *Place of birth* | "What is your state in Mexico or country of birth?" | | | Same state; other state; other country; in the US. |
| *Place of residence...* | | | | |
| ...1 year ago | Inferred from data by comparing residence of respondents the previous year. | Not available | "Where did you live 1 year ago?" | Same state; other state; other country. |
| ...5 years ago | Not available (panel is 1.25 years) | Where did you live 5 years ago? | | |
| | | **Emigrant definitions** | | |
| *Emigrants during last...* | | | | |
| ... 5 years | Inferred by grouping all migrants within the previous five years. | "Name all the household members who have left the country in the last 5 years." | | All countries except Mexico. |
| ... year | Inferred by grouping all migrants within the last year. | From "What was the year of emigration?" restrict to emigrants from the previous year. | | All countries except Mexico. |

Therefore, the immigration panel combines international immigrants and internal movers. Since all respondents are asked about their place of birth in Mexico or outside, I compare it to their current residence. If they are different, they are labeled 'Other state', 'Other country' or 'U.S.', otherwise they are labeled 'Same state'. This measure of immigration is useful to understand immigrant stocks rather than flows. For immigrants by place of residence, I can only compare the place of residence relative to one year ago because ENOE respondents are only surveyed for up to five consecutive quarters, and there is no information for location five *years* prior. This is why there is no comparison to the Census, only to the ENADID. To identify the location a year earlier, I look at households that were in their fifth and last survey in the comparable ENADID quarter. Then, we track respondents from those households to their responses a year earlier (during the household's first interview). People that are matched are labeled as 'Same state'. Not everyone is matched because some people leave or arrive between interviews two to four. We look at people who entered the household in interview two;[8] they are labeled 'New residents' and their broad origin is recorded in the ENOE. This comparison is only possible for respondents at least one year old during interview five.

As for people moving out of places, I focus on international emigrants. The ENOE is not a retrospective survey like the migration modules of the Census and the ENADID. The Census and ENADID collect information on all migrants from a household who left during the last five years, and their year of emigration. The best comparison using ENOE migrants, is to select all migrants within the year and 5 years of the Census or ENADID period. This is not a perfect comparison because households in the ENOE with any migrants may have had migrants in the past (i.e., the last five years) which are not reported.

To analyze lifetime immigrants and international emigrants, I use the collapsed version of the ENOE. For immigrants by recent residence I use the 1-year long panel of the ENOE. These definitions provide the subgroups of the data to compare. For the actual metric of comparison, I rely on variables that are found in all data: share of female migrants, mean age of migrants and distribution of migrants across locality size.[9] Since all immigrants, regardless of their definition, answer the census or ENADID there are more variables that could be compared, but for consistency and space I limit the analysis. Shares and means are calculated using the *svydesign* package in R which takes into account the survey structure and estimates standard errors. For ease of exposition, I graph the statistics but include the estimates and standard errors in section A.4 of the appendix.

Finally, I calculate the root mean square error (RMSE) between the ENOE and the comparison data ($j = \{ENADID, Census\}$) value over all years ($t \in \{2009, 2014, 2018\}$ for $j = ENADID$, $t \in \{2010, 2020\}$ for $j = Census$). The objective of this step is to quantify the difference in point estimates. The lower the RMSE, the closer the point estimates are. As a benchmark, I present the RMSE between ENADID and Census by comparing the 2009

[8]New members to a household in interview 2 were in a different place in interview 1, which is exactly one year before interview 5. Moreover, in the first interview, no one can be registered as a 'New resident' by construction.

[9]Localities are binned by population size: less than 2,500 people, 2,500-14,999 people, 15,000-99,999 people, and over 100,000 people.

or 2018 ENADID values to the 2010 or 2020 Census values, respectively.

$$RMSE = \sum_{t}^{T} \sqrt{\frac{(y^{ENOE,t} - y^{j,t})}{T}} \tag{1.1}$$

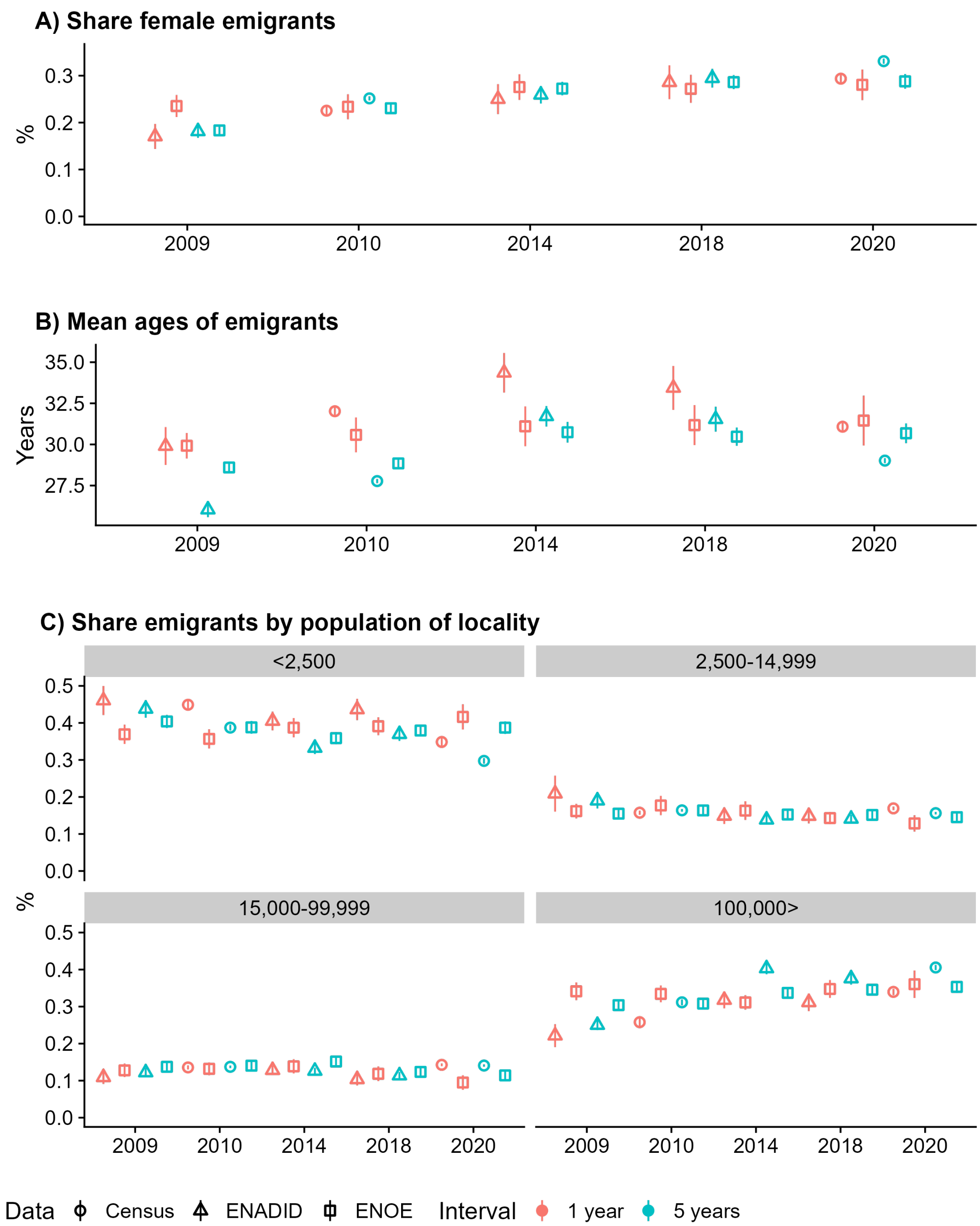
### 1.4.2 Results

Figures 1.1 through 1.3 show the descriptive statistics with a 90% confidence interval. Figure 1.1 shows that most international emigrants are i) male but that this share is decreasing over time (panel A); ii) on average between 27 and 33 years old, but there is an upward trend (panel B); iii) and that the majority of emigrants come from less-populated municipalities (panel C). In general, there is an overlap between data, but there are a couple of noticeable patterns. For instance, the longer 5-year shares of female emigrants are similar between the ENOE and ENADID, but the 1-year estimates are more similar between the ENOE and Census. In terms of age, the ENADID and Census tend to have older (younger) migrants than the ENOE for the 1-year (5-year) measurement. In 2009 and 2014, the ENOE had fewer emigrants in small communities ($< 2,500$) but more emigrants in large communities (+100,000) relative to the other data. Towards the end of the period, the pattern flips and the ENOE reports more very rural emigrants and fewer urban emigrants relative to the Census.

Figure 1.2 shows that 80% of people live in the state where they were born. A small share of foreign-born reside in Mexico: between 0.5% of U.S.-born and 0.2% from other countries. This composition has not changed over time and is consistent across data. There is substantial overlap in the share of female migrants and mean age across data. However, I include the estimate for those with an unspecified birthplace to show that missing observations are not similar across the household surveys.

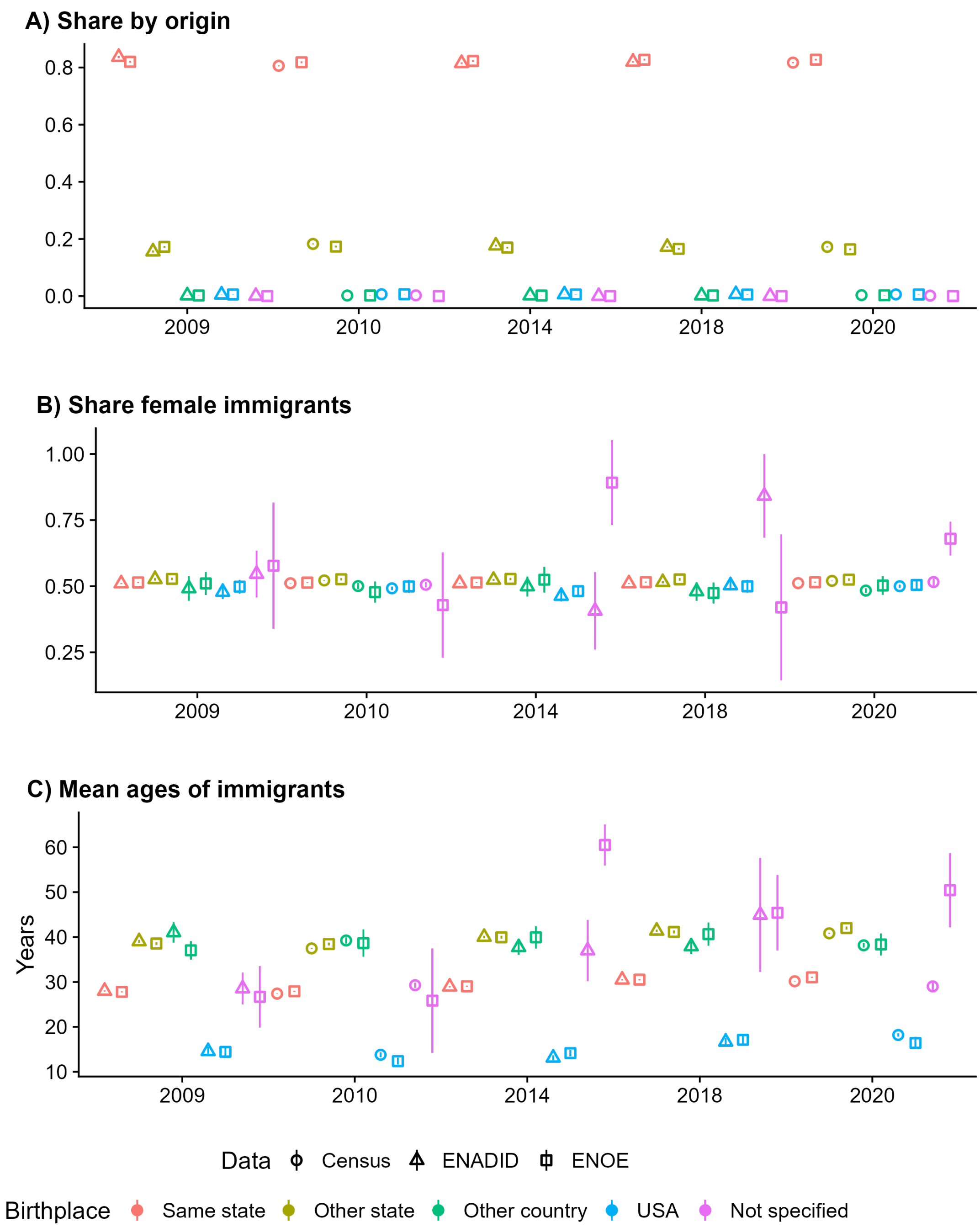
For immigrants by recent place of residence, I only compare the ENOE to the ENADID. Figure 1.3 suggests that in the short-run almost all people remain in the same state. This may be unusually high because it includes people who moved within the state. Similar to Figure 1.2, the ENOE aligns in the share of female immigrants and mean ages, but shows a discrepancy in the missing values.

**Figure 1.1:** Characteristics of **international emigrants** in the ENOE, ENADID and Census.



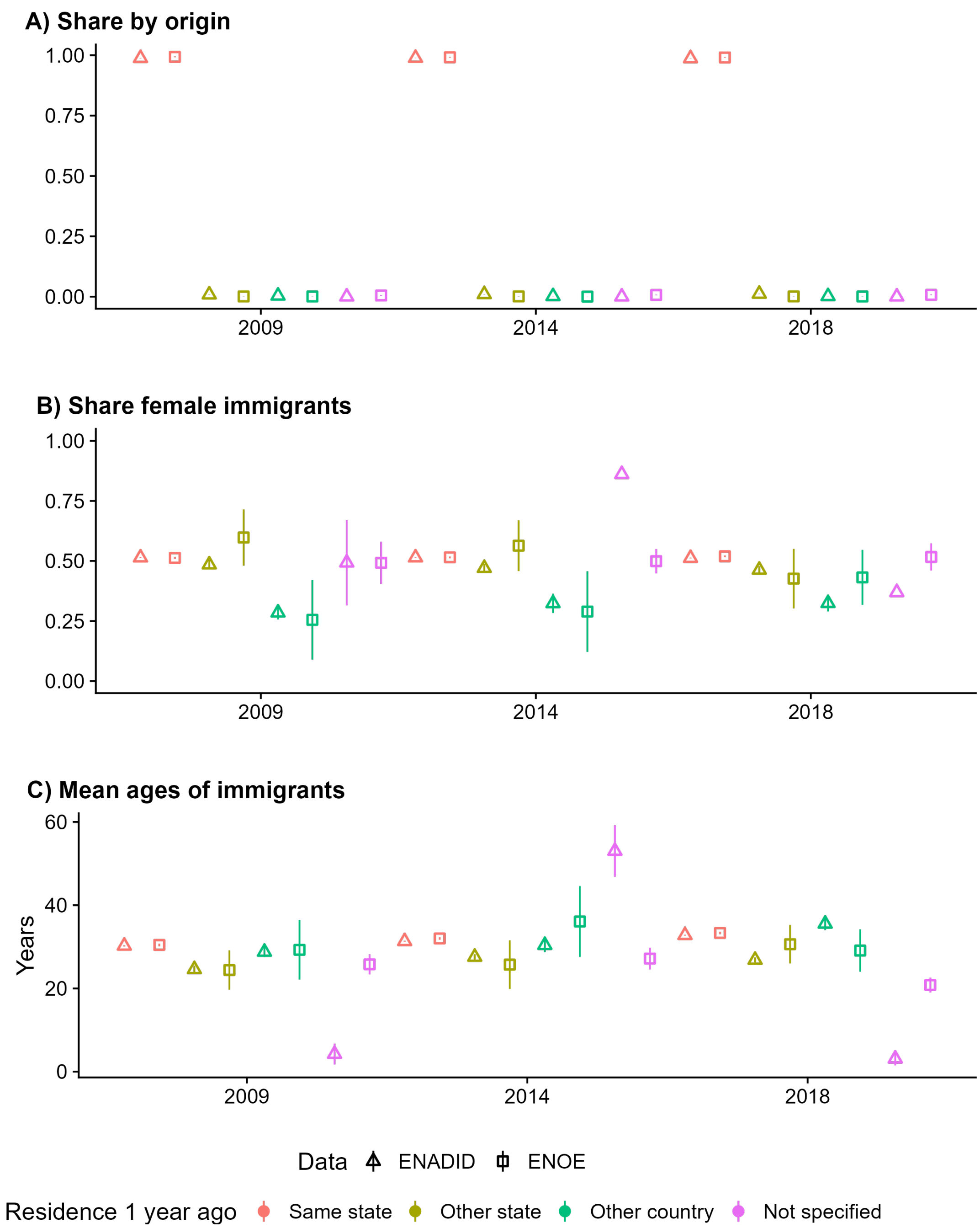

Source: Own calculations using the 2010 and 2020 Census from Mexico, the 2009, 2014 and 2018 ENADID and the ENOE during comparable quarters. All data publicly available through INEGI.

**Figure 1.2:** Characteristics of **immigrants by their place of birth** from the ENOE, ENADID and Census.




Source: Own calculations using the 2010 and 2020 Census from Mexico, the 2009, 2014 and 2018 ENADID and the ENOE during comparable quarters. All data publicly available through INEGI.

**Figure 1.3:** Characteristics of **immigrants by residence 1 year ago** from the ENOE and ENADID.




Source: Own calculations using the 2009, 2014 and 2018 ENADID and the ENOE during comparable quarters. All data publicly available through INEGI.

To complement this visual inspection, table 1.2 shows the RMSE between data for each variable. The RMSE aggregates the differences between estimates over all years. For the ENOE to be similar to the other data, its RMSE should be less than the benchmark (the ENADID-Census RMSE). This is true for international emigrants since for all but one variable (population larger than 100,000) at least one ENOE-based RMSE was smaller than the benchmark.

For immigrants by place of birth, the ENOE-based RMSE in share female and mean age do worse than the benchmark in column (3). This is true even when removing the 'Not specified' groups (results available in appendix A.5). Interestingly, the share female from the ENOE has a smaller error relative to the Census, than to the ENADID. Lastly, the ENOE-ENADID RMSE for immigrants by recent residence if similar to the RMSE of immigrants by birthplace.

**Table 1.2:** Root Mean Square Error for all yearly observations within migrant categories and variables.

| Variable | ENOE vs ENADID (1) | ENOE vs Census (2) | ENADID vs Census (3) |
|---|---|---|---|
| **International emigrants** | | | |
| Share female | 0.0297 | 0.0252 | 0.0483 |
| Mean age | 2.0147 | 1.2383 | 2.2023 |
| Share by size of locality | 0.0419 | 0.0470 | 0.0430 |
| <2,500 | 0.0460 | 0.0727 | 0.0625 |
| 2,500-14,999 | 0.0259 | 0.0232 | 0.0316 |
| 15,000-99,999 | 0.0166 | 0.0275 | 0.0283 |
| 100,000< | 0.0631 | 0.0475 | 0.0411 |
| **Immigrants by place of birth** | | | |
| Share by origin | 0.0070 | 0.0066 | 0.0129 |
| Share female | 0.1665 | 0.0582 | 0.1040 |
| Mean age | 6.2515 | 6.9296 | 5.1392 |
| **Immigrants by residence 1 year ago** | | | |
| Share by origin | 0.0060 | | |
| Share female | 0.1255 | | |
| Mean age | 11.3270 | | |

Altogether, these findings imply that the composition of migrants from the ENOE is similar to the ENADID and the Census. For instance, international emigrants within the last year in the ENOE are a good proxy for 1-year emigrants in the Census. The similarities are more promising for international emigrants than for immigrants since there is less of an overlap in the latter with the gold-standard data. However, even the ENADID is not exactly comparable as their RMSE is not 0. In the next section, I compare migration rates from the ENOE.

## 1.5 Comparing Migration Rates

This section provides estimates and them to those published by Mexico's National Population Council (CONAPO). The 2023 *Conciliación Demográfica de México, 1950-2019* (Demographic Conciliation of Mexico)[10] contains retrospective estimates of fertility, mortality and migration for Mexico, its states and municipalities. It provides a detailed account of the demographic situation of Mexico from 1950 until 2019 and forecasts of demographic trends until 2070. CONAPO's migration estimates come from a mix of data from Mexico and the U.S.. For instance, they used Mexican censuses and the 2015 intercensal survey to obtain the population who was absent. Then they complement the 5-year counts by using the American Community Survey (ACS) and U.S. censuses to determine how many Mexican-born individuals migrated within the last year of the ACS or years between censuses. These sex and year-specific counts are smoothed using demographic techniques: first, with a Rogers-Castro age-specific migration model, then the age structure is standardized using the Brass method. Appendix A.6 summarizes the traits of CONAPO's estimates and the ENOE.

To estimate migration rates from the ENOE, I follow guidelines from Instituto Nacional de Estadística y Geografía (2012) and Paredes and Mera-Ceballos (2012). Migration rates are given by equation 1.2: the numerator is the weighted migrant count and the denominator is the total exposure of people surveyed and then weighted to represent the total population. $M_{i,j}^t$ is the total number of migrants in year $t$ that originate in $i$ and move to $j$. In this notation, emigrants are $M_{Mex,j}^t$ and immigrants are $M_{i,Mex}^t$. While a person can move across borders multiple times, in this rate we count migrants rather than events. Observations are weighted by the survey weight $f_k$ which is the same for all respondents within a household. In terms of exposure, the assumption is that a resident of the survey lives the full quarter (0.25 years) while a migrant only lives on average half of the quarter (0.125 years). A respondent who was been surveyed during 4 consecutive quarters of a year will have an exposure of $0.25 \times 4 = 1$ year.

$$
\begin{aligned}
m_{i,j}^t &= \frac{M_{i,j}^t}{PYL^t} \\
&= \frac{\sum\limits_{k\in R} \mathbb{1}(k = Migrant, t) \times f_k}{\sum\limits_{k\in R} \underbrace{\mathbb{1}(k = Resident, t) \times 0.25 \times f_{k,t}}_{\text{exposure of permanent residents}} + \underbrace{\mathbb{1}(k = Migrant, t) \times 0.125 \times f_{k,t}}_{\text{exposure of emigrants and immigrants}}}
\end{aligned} \tag{1.2}
$$

Yearly migration rates are calculated by pooling all ENOE waves. Instituto Nacional de Estadística y Geografía (2012) recommends using only observations that are uniquely identified across waves to create a Common Sample (CS). As observations are dropped (specifically, observations from the first interview[11]), the household weights have to be re-estimated. They recommend using a constant such that the sum of survey weights in the

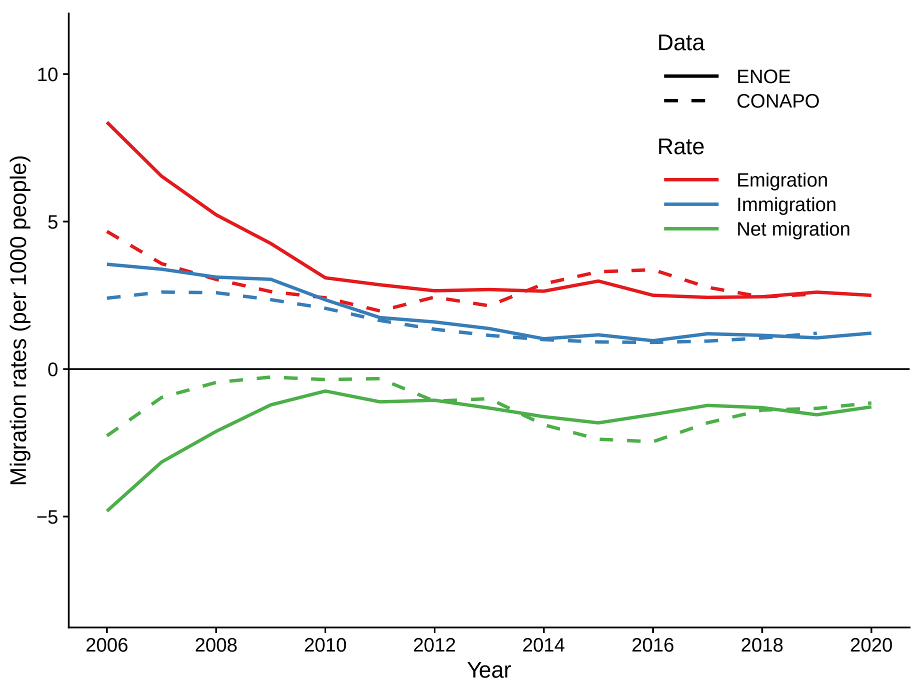
[10] https://www.gob.mx/conapo/acciones-y-programas/conciliacion-demografica-de-1950-a-2019-y-proyecciones-de-la-poblacion-de-mexico-y-de-las-entidades-federativas-2020-a-2070

[11] Although it's not explicit in Instituto Nacional de Estadística y Geografía (2012), my understanding is that you don't want to include those in the first interview because their location prior to that interview is unknown. The CS only has people that are exposed to migration (i.e., they have to be part present in the previous period as well.

CS is equal to the mid-year population of the geographic unit of analysis. For the main results, I do not use the common sample but rather use all the available observations and the original survey weights. Appendix A.7 contains all figures shown in here but uses the common sample. Qualitatively the results are similar to using all available observations.

Figure 1.4 shows that migration rates from the ENOE and CONAPO depict similar patterns: the emigration rate is larger than the immigration rate leading to a negative net migration rate. However, ENOE rates are substantially larger until around 2012. Afterwards, all ENOE rates fluctuate but are within 1 per 1000 from CONAPO rates. The ENOE emigration rate has a parallel trend to CONAPO's estimates up until 2010, and afterward the gap decreases. For the immigration rates, the ENOE estimates closely follow those of CONAPO.

**Figure 1.4:** Migration rates between the ENOE and official estimates from CONAPO




Source: CONAPO and own calculations for ENOE rates.

Possible reasons for the difference between the rates lie in i) the definitions of the exposure to migration and the counts of migrants, ii) the timing of the interview and iii) the attrition in the ENOE of households where all the members migrate. The latter two reasons are analyzed in detail in appendix A.8. The ENOE records someone as absent if they were permanently absent relative to the last quarter while CONAPO's estimates come from yearly data. Therefore, ENOE estimates may capture less permanent migration such as seasonal migration.

For immigrants to Mexico, the ENOE and CONAPO rates are surprisingly similar. As a household survey, the ENOE cannot observe immigrants who are passing through Mexico or who do not have a temporary address. Therefore, the immigrants who we observe are likely to have some connections to Mexico or they may be permanent immigrants. Another option is that they are return migrants or children of migrants. The immigration rates may be similar because of similar limitations in surveys and censuses in observing temporary or permanent migrants.

Another difference is that CONAPO estimates the number of emigrants using the counts of people who reported having migrated within a year from the ACS. While the ACS is a nationally representative survey, it may not fully capture Mexican immigrants, especially those who are undocumented, live in grouped quarters, or are seasonal workers. Moraga (2011) suggests that there is an important undercount of migrants in the ACS, which could explain why the CONAPO emigration rate is smaller than the ENOE's.

Despite these differences, and the fact that the inputs for the ENOE and CONAPO rates are distinct, a takeaway is that the rates are fairly similar in more recent periods. This is encouraging because the ENOE may potentially be used for more timely migration estimates.

## 1.6 When to use the ENOE?

The results suggest that the ENOE can provide comparable estimates on demographic characteristics of migrants and follows aggregate trends of official migration sources. However, the ENOE has advantages and limitations that migration researchers should be aware of.

The ENOE is particularly helpful to analyze demographic and economic variables that are not present in other data. For instance, education of all migrants is available in the ENOE while in the Census education (and other variables) is only recorded for return migrants (as education is not part of the migration module, and must be reported by respondents at the time of the Census). Since the ENOE is a labor force survey, it collects information about employment conditions (type, payment frequency, work benefits, structure) and unemployment time. It also has information about the people outside of the labor force, which allows migration researchers to analyze the non-economic factors of migration, and age-ranges (the young and the old) that are often dismissed. Nevertheless, since the ENOE questions are not formulated around migration there are core questions missing. The ENOE has no information about the specific destination/origin of a migrant and it only informs about moves to/origins from 'Another country', 'Other state' or the 'Same state'. If researchers are interested in the destinations/origins of a migrant, the ENADID and Census are better suited. In particular, the ENADID asks about the specific U.S. state of destination, and even distinguishes between the state at first arrival, the current state and the state before they returned to Mexico (if they are return migrants). Despite the lack of origin-destination information of the ENOE, it can be used to answer questions related to selection into migration based on employment, income and education. More importantly, it is likely that characteristics of migrants are accurate because they are reported by the migrants before they leave (rather than by a household member time after the migrant left).

Another advantage of the ENOE is the quarterly frequency and the panel structure. The ENADID and the Census collect information every 4 or 10 years, respectively, and supplement this by asking about migration within the last 5 years. A problem with this approach is that only households who remain in Mexico will be interviewed. The ENOE is more frequent thereby making it more likely that households who leave (and are sampled) leave some information behind. Moreover, INEGI has guidelines to reduce non-response which leave information about households who moved away (Instituto Nacional de Estadística y Geografía, 2009, p.70). ENOE interviewers visit households in person and may visit multiple times if nobody is available or able to respond to the survey in the first visit. If on the fifth visit, there is no contact with the sampled household, then interviewers will collect information about the household from neighbors and observe the state of the building. Interviewers record these observations in broader categories, which allows researchers to identify some household that migrated all at once. This shows the high quality and standards for data collection at INEGI.

Related to the frequency of the data, the ENOE can be merged with other data to understand how fluctuations in conditions (i.e., economic, climate or social) can affect migration. For instance, for the analysis of the next two chapters, I add the municipality and time-specific drought index,[12] remittances received by states per quarter and the shortest distance from municipalities to the U.S.-Mexico border. When adding other data, researchers should be careful to remember that the ENOE is only representative at specific levels (state, 'self-representative' city, rural/urban divide and by categories of size of locality). As a result, it is not advised to carry out any analysis where the unit of observation is the municipality.

Despite its advantages, migration researchers should be careful when using the ENOE to calculate migrant counts. Paredes and Mera-Ceballos (2012) and Instituto Nacional de Estadística y Geografía (2012) emphasize that for international emigration, the ENOE should only be used to calculate weighted rates or shares. Indeed, the weighted counts of international emigrants from the ENOE in figure A.7 (Appendix A.9) are larger than those of the Census or ENADID. This difference is very large when the counts are aggregated over five years. One reason for this discrepancy is that weights should add up to the total population in Mexico, but in the ENOE the weights add up to the total population in Mexico plus the recent migrants. This may partially explain the difference in the migration rates from CONAPO.

Since international emigration is not common, researchers should not calculate migration rates (or shares within migrants) by quarters (Paredes & Mera-Ceballos, 2012). Instead, researchers should group quarters within years or longer periods. Adding to this, calculating migration shares in disaggregated spatial units (municipalities, localities or smaller) should be avoided as many places have no migrant counts and would only yield estimates with large standard errors. Instead, researchers should use states or regions. To this list, I also add disaggregating by exact ages, and years of education.

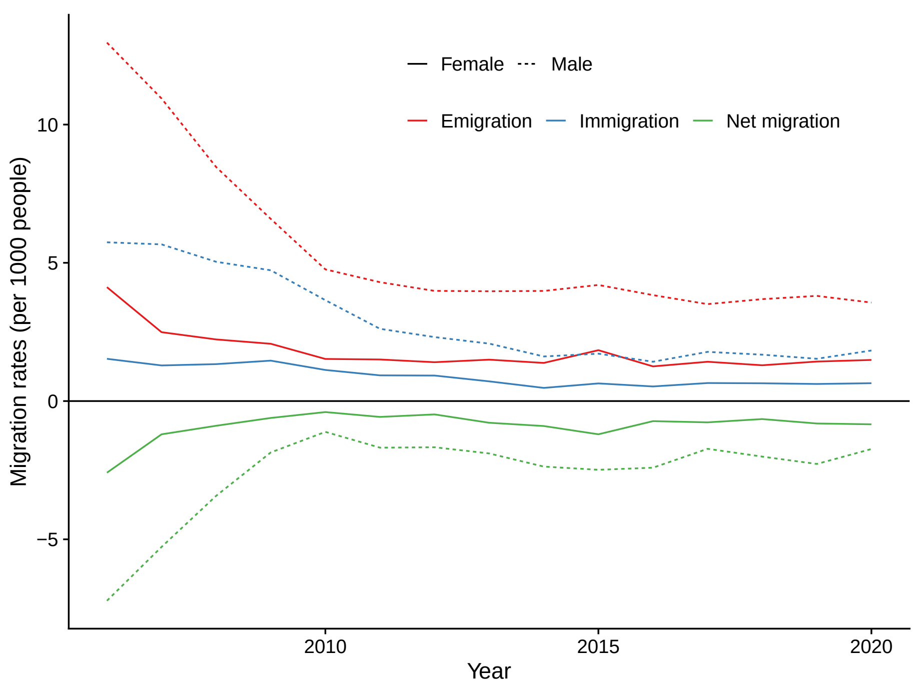
Finally, the ENOE has the advantage of being a panel survey. The information during the five consecutive quarters can shed light into short-term changes within migrants. For instance, Bertoli and Murard (2020) analyse how international migration is related to changes in household composition in the immediate future. The panel setting would allow for causal analysis since changes in outcomes could be analysed before and after an exogenous event. On this note, the only limitation is that migration may not be an outcome since there is no post-migration data. Instead, researchers may be interested in how outcomes of households with migrants react to a change. In this sense, for causal analysis on migration, migrants are the subsample rather than the outcome of interest.

[12] Published by the National Meteorological Institute of Mexico.

Altogether, when should migration researchers use the ENOE? The ENOE contains useful information for demographic and economic characteristics of emigrants before they leave Mexico and of immigrants after they enter Mexico. This data is a valuable source of information for specific, frequent and detailed variables on economic and demographic characteristics of a panel of respondents. This panel is nationally representative and captures migrants such that their demographic composition is comparable to the Census and the ENADID. Moreover, if researchers are interested in trends, the ENOE has the potential to detect changes in migration trends even before official estimates (which may need demographic modeling and are not updated frequently).

As an example of the benefits of the ENOE, figure 1.5 shows the migration rates for women and men. Emigration from Mexico has been male-dominated for most of its history. A surprising result is that the immigration rate is also very large, and even larger than the female emigration rate. Male rates have a steeper decline than female rates, particularly before 2010, which is consistent with the effects of the 2008 Financial Crisis. Female rates, although lower than male rates, are relatively consistent. Without the ENOE it would be possible to obtain only estimates for some of these years and we would miss on the fluctuations in the sex-specific migration rates. Chapter three of this dissertation explores these trends and the relative changes between female and male migrants, which is possible because of the available variables from the ENOE.

**Figure 1.5:** Migration rates from the ENOE by sex over time



## 1.7 Conclusions

Relative to many countries, Mexico counts with numerous types of high-quality migration data. Migration modules in the ENADID and Census have allowed extensive research on migration. Despite the success of these data, they often need to be complemented with other data to answer research questions. One important shortcoming of these data is that they capture few demographic and almost no economic characteristics of migrants, which are fundamental for research in migration.

One alternative is the ENOE. Although the ENOE is not designed for migration, the results from previous sections show that it is a reliable source of information on migrants. Demographic characteristics of migrants in the ENOE are comparable to those in the census and the ENADID. Rather than fielding a new demographic survey, the ENOE is an adequate alternative to understand composition of emigrants and immigrants by residence. To my knowledge this is the first validation of the ENOE that encompasses emigration and immigration. The breadth of data from the ENOE makes it an attractive option, to answer older questions with newer data: are migrants negatively selected in terms of income (an update to work by Moraga (2011))? Does prevalence of migration help predict individual migration? How does migration react to shocks? This data can also help answer new questions. For instance, the quarterly frequency can allow researchers to integrate environmental and agricultural factors to understand finer-scale responses to changes in climate. Another area of opportunity would focus on internal migration and produce metrics on population redistribution from the ENOE à la Bell et al. (2015).

Using the ENOE comes with its considerations for researchers. This paper adds to the literature by providing guidelines in section 1.6 for researchers interested in migration data from Mexico. Particularly, the ENOE should be used when research questions deal with i) the characteristics or experiences of migrants in Mexico, and ii) understanding trends in migration rates. The fact that the ENOE is not designed as a demographic survey is a feature rather than a limitation, since the panel structure can help with causal research designs. Overall, the ENOE is an adequate source of migration information, especially when no other data has its breadth and frequency.

# Chapter 2

# Ready to move? Examining the relationships between migration preparations, actual migration, and employment outcomes in Mexico

## 2.1 Introduction

In spite of the rising numbers of international migrants reported globally, only about 3.6% of the world population is classified as an international migrant.[1] Research on migration aspirations (Carling & Schewel, 2018; De Haas, 2021) highlights that much larger numbers of people would like to move internationally, which means that many people find themselves in a situation of "involuntary immobility" (Carling, 2002), i.e. with unrealized migration aspirations for a lack of ability to migrate. A full investigation of decision-making in migration processes must hence consider several positions in the migration aspirations and capabilities nexus (De Haas, 2021). This encompasses looking at those who aspire to move (or not; see Schewel (2020)) and, among these, both at people who are able to migrate, and those who are not (Carling, 2002; Carling & Schewel, 2018; De Haas, 2010, 2021).

Research on migration aspirations, and particularly on the link between migration aspirations and capabilities, is a growing area of academic interest De Haas (2021).[2] Most of this vast research on migration aspirations has looked at the motivational components of considering migration, especially at the determinants of forming intentions to migrate. Some studies even delve into the likelihood of migrating within a given timeframe (for an overview of these studies, see Carling and Schewel (2018)). But, as highlighted by Kley (2011), between the consideration (development of migration intentions) and the realization of migration (actual mobility), we can find a stage of migration plans or preparations. This phase includes volitional steps that ensue (or not) the formation of migration intentions and

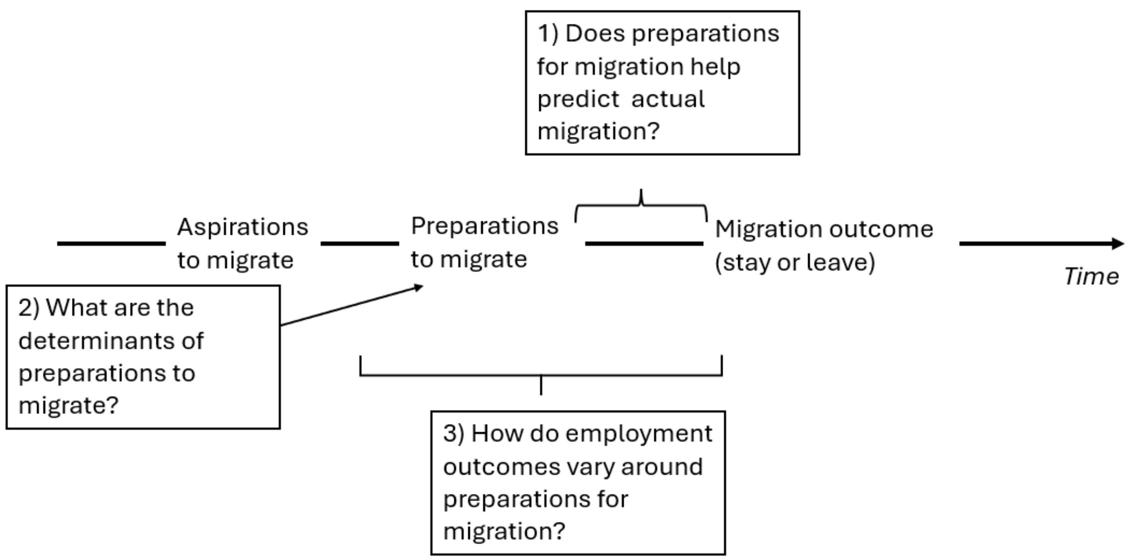
[1] According to data from the International Organization for Migration (IOM) data portal (https://www.iom.int/data-and-research), accessed on June 20th, 2024.

[2] The rising number of journal special issues on the topic of migration aspirations is a testament to this (for example, Bal and Willems (2014), Carling and Schewel (2018), and Robertson et al. (2018)).

include action towards the manifestation of such migration intentions into actual migration. These volitional steps can include concrete actions like applying for a visa, contacting travel agencies, purchasing plane tickets, or searching for a job in a country of choice. Though it has been acknowledged as an important and even necessary step in the migration process (Kley, 2011), this preparatory phase has not received much attention in the migration literature.

Using rich panel data from Mexico between 2005 and 2019, we set out to research migration plans or preparations. Specifically, we advance three research questions: (1) if, and how, preparations and actual migration are linked, and how long preparations tend to last; (2) what are the sociodemographic and structural determinants of migration preparations; and (3) whether the development of migration preparations is related with employment outcomes and one's participation in the labor force. Altogether, these questions aim to holistically understand the dynamics and constraints of engaging in migration preparations, and how preparations are related to actual migration and structural employment outcomes. By answering them, we hope to contribute directly to the growing literature on migration decision-making and, particularly, on the aspiration-capabilities framework (De Haas, 2021). Additionally, by looking at the relationship between migration and employment outcomes, our last question taps into the links between migration and (community) development (De Haas, 2010). Figure 2.1 illustrates how our questions relate to the migration-decision process.

**Figure 2.1:** Research questions within the migration decision-making framework




Source: Own elaboration based on Kley (2011).

Our analysis suggests that long-lasting migration preparations are a relatively rare event, even among those who eventually end up migrating. Thus, and according to our data, engaging in formal preparations to migrate for an extended period is not an essential stage in the migration process. In addition, most of the people who plan to migrate internationally are usually in this stage only for a relatively short period, typically migrating within three months. In what pertains to the sociodemographic and structural determinants of preparing to migrate, we also find some noteworthy trends. Identifying as male, living in historically migrant-sending regions, acting as a household head, and belonging to remittance-receiving households are all associated with higher odds of preparing to migrate. However, we find a gradient in education where having graduate studies is associated with higher odds of preparing to migrate. Finally, we used event studies to examine the relationship between migration preparations and employment outcomes. Our analyses suggest that preparing to migrate occurs in times of unemployment. Then income, hours worked and the probability of working in the informal sector fluctuate distinctly between people for whom preparations materialize on actual migration, and those who, despite undertaking preparations, do not migrate (at least within the timeframe of the survey). The latter begin preparations in times of income instability, while the former work more and transition into the informal market after reporting planning to migrate. We further discuss these results, how they fit the existing research on migration decisions, as well as possible limitations of the analysis, in greater detail below, after presenting the theoretical framework guiding our work and the data we used.

## 2.2 Preparations and the migration decision-making process

The last few years have been prolific in studies on the "internal dynamics of migration processes" (De Haas, 2010), i.e. on the social mechanisms that facilitate or undermine migration. As argued in such studies, these mechanisms operate at different stages of the migration process and at varied times in one's life course, often far preceding migration movements per se (Carling, 2002; De Haas, 2021; De Jong, 2000; Kley, 2011). These insights are at the heart of the migration aspirations-capabilities framework (De Haas, 2021). Per this theory, the outcomes of migration processes result from the (sequential) combination of migration aspirations and capabilities, possibly leading to several different migration outcomes (Carling, 2002; Carling & Schewel, 2018; De Haas, 2010; Schewel, 2020).

Earlier migration theories tended to focus especially on actual migration, considered as a proxy for migration capabilities (De Haas, 2010). The expansion of the aspirations-capabilities thesis in the last decades has been accompanied by a growing concern about the causes of developing aspirations to migrate. There is hence now a vibrant scholarship on the individual and ecological determinants of migration aspirations (e.g. Bal and Willems (2014), Carling and Schewel (2018), and Robertson et al. (2018)), and about whether and how migration aspirations are predictive of actual migration. There is some work showing that migration aspirations are linked to actual migration flows. For example, Tjaden et al. (2019) find a measurable and systematic macro-level relation between intentions to migrate and actual migration flows. This claim is supported and qualified by van Dalen and Henkens (2013), who show that this relation depends on features like individual human capital, social forces, personality traits, or the quality of public organizations. Therefore, a full understanding of migration processes is better achieved by studying, not only migration capabilities but also preceding stages, such as migration intentions or preparations.

Migration intentions, preparations, and capabilities have been theorized as constituting a process involving multiple stages of action and decision-making (Boccagni, 2017; De Jong, 2000; Kley, 2011; Koikkalainen & Kyle, 2016; Pine, 2014; Vigh, 2009). These works see migration processes as composed of an expected sequence of events that may eventually lead to migration once all the steps are observed. Kley (2011) arguably offers one of the most systematic explanations of these steps in her account of how the stages of migration take place across the life-course of (potential) migrants (De Jong, 2000). Kley (2011) considers three main stages present in all migration actional and decision-making processes.[3] The first stage refers to the consideration of migration. In this motivational (aspirational) phase, the potential migrant develops desires or intentions to migrate. These aspirations are eventually molded into a third actional step, where migration is realized (i.e. where migration abilities are expressed), but not without experiencing a transitional (second) stage. This phase, which Kley (2011) names the pre-actional phase, is where the enactment of plans (i.e. preparations) for migration takes place. Kley (2011, p. 471) depicts this phase as crucial and likely to lead to actual migration, because *"[t]he actor is then striving for making his or her goals come true. Therefore the making of concrete plans for certain behaviour is an indicator for having decided to act in a certain way. In this pre-actional phase, abandoning intentions or plans is costly."* Judging from this, the planning or preparatory stage is therefore relevant in its own right, providing a necessary connection between the motivational or aspirational stage and the actual realization of migration (capabilities). Our work focuses specifically on the preparatory phase of the migration decision-making process. Despite its acknowledged importance (Kley, 2011), this phase has been much less investigated than other phases, such as migration aspirations or intentions, or migration abilities and actual migration movements.

Several factors have been shown to influence the development of migration aspirations and intentions. Reviewing these briefly may prove instructive for signaling potential correlates of the other pre-actional stage of migration decision-making: migration preparations. Research has found that higher perceived crime, violence, or fears for personal safety (Blacklock et al., 2014; Wood et al., 2010), life dissatisfaction and perceived threats to current livelihoods (Cai et al., 2014; Chindarkar, 2014; Groenewold et al., 2012; Ivlevs, 2015; Lu, 1999; Migali & Scipioni, 2019; Otrachshenko & Popova, 2014), or perceived gender discrimination (Ruyssen & Salomone, 2018) in communities of origin have been linked to higher probabilities of developing aspirations to move. Perceptions of the conditions of life at the destinations also matter, as discussed, for example, in Becerra (2012), Blacklock et al. (2014), Hoppe and Fujishiro (2015), and Sancho (2017).

Beyond perceptions, real settings matter too. Migration aspirations depend on access to public services and desire for amenities (Dustmann & Okatenko, 2014), Internet use (Thulin & Vilhelmson, 2014; Vigh, 2009), the quality of democratic structures (Hiskey et al., 2014), armed conflicts (Efendic, 2016), political discontent (Etling et al., 2020), and food insecurity (Smith & Floro, 2020). Dissimilarities in aspirations have also been identified as resulting from ethnic-specific subjectivities, as emphasized by Agadjanian et al. (2008) for Kyrgyzstan. There is also much research in the sociology of emotions, as well as in social psychology, on how migration aspirations are related to specific emotions and personality traits (Boneva &

[3] Kley (2011) also considers a fourth (post-actional) stage where migration outcomes are evaluated at the destination, which may lead to a re-cycling of the previous stages. We omit this stage since it is a later phase of the migration decision-making process than the ones we are focusing on in this paper.

Frieze, 2001; Frieze et al., 2006; Rodan & Huijsmans, 2021; Williams et al., 2018). Lastly, migration ties and experiences, like living in a community where migration is common, can also foster migration aspirations. Prior experiences as a migrant are related to positive odds of having aspirations to migrate again in the future (Ahlburg & Brown, 1998; Czaika & Vothknecht, 2014). Even for individuals with no prior migration histories, holding ties to extant migrants leads to an increase in migration aspirations (Manchin & Orazbayev, 2018; Marrow & Klekowski von Koppenfels, 2020; Van Mol et al., 2018). Also, together with having migration networks (Garip & Asad, 2016), the existence of a "culture of migration" influences the development (or not; see Timmerman et al. (2014)) of intentions to migrate (Alpes, 2014; Becerra, 2012; Kandel & Massey, 2002).

Focusing specifically on our case study, relatively few papers have quantitatively looked at micro-level pre-migration dynamics, or linked migration aspirations and capabilities, for the case of Mexico. Kandel and Massey (2002) analyze the aspirations to migrate to the United States for work (or to live) of youth in the state of Zacatecas, and its link to school-related outcomes. They find that family involvement is related to higher odds of having aspirations to migrate, and that these aspirations decrease the odds of deciding to stay in school. Becerra (2012) also focuses on youth, but in the city of Tijuana, and asks whether perceived discrimination towards Mexicans in the United States deters those youth from having migration aspirations. Higher levels of perceived discrimination are related to lower probabilities of having aspirations to migrate. However, this is not true if migration is associated with the belief that they must support their families. Using the Mexican Family Life Survey, Chort (2014) and Creighton (2013) also analyze the determinants of aspirations. Creighton (2013) follows a two-step analysis to look at potential migrants, and analyzes if aspirations can predict internal and international migration from Mexico. The author finds that aspirations to migrate internationally may be predicted by being male, having strong family ties abroad, more neighborhood crime, and higher educational levels. Aspirations are in general predictive of future migration. Chort (2014) focuses on the gendered determinants of aspirations and tests their stability to several ecological shocks. The results show that women are less likely to have aspirations to migrate than men. This stands as an important example of how examining selection into migration aspirations can complement the extant literature on selection into actual migration in Mexico (Chiquiar & Hanson, 2005; Moraga, 2011; Rendall & Parker, 2014). In any case, as for the larger literature on the pre-migration phases, the majority of the works on the antecedents of migration in Mexico have focused on the motivational or aspirational phase. In other words, to our knowledge, migration preparations have not been granted individualized attention by previous works focusing on Mexico.

In our paper, we address the previous gap in the literature and empirically analyze this crucial preparatory stage. By doing this, we aim to address the (relative) absence of knowledge on the dynamics surrounding migration preparations. Particularly, we examine if, and how, preparations are indeed needed for the realization of migration capabilities, as formally posited by Kley (2011), and indirectly highlighted by others (Frieze et al., 2006; Sancho, 2017; Thulin & Vilhelmson, 2014). Moreover, we also aim to understand more about the temporality and dynamics of this preparatory stage of the migration decision-making process, particularly whether there are indications of self-selection into engaging in migration preparations. Comparing our results with those of the literature on the determinants of selection into aspirations reviewed above, will prove interesting for a deeper understanding of how these two stages are different in practice. In addition, and since the data we use come from a survey of the labor force, we are also able to tap into whether engaging in migration preparations is associated with employment behaviors (see Kandel and Massey (2002), for a similar connection regarding attitudes towards education). Such questions have mostly remained unanswered thus far concerning the planning or preparatory phase of the migration process. Furthermore, by providing key quantitative information on a crucial, yet less-known stage of the migration process, we also aim to provide a better knowledge of migration decision-making dynamics in general.

## 2.3 Data and Methods

We use the *Encuesta Nacional de Ocupación y Empleo* (ENOE), which is the publicly available Mexican Labor Force survey. This dataset primarily measures quarterly employment changes in Mexico and is carried out by the *Instituto Nacional de Estadística y Geografía* (INEGI). The ENOE is a longitudinal survey that follows a nationally representative sample of households in Mexico over five quarters. By pooling all observations from the first ENOE survey wave (2005) until the fourth quarter of 2019,[4] our initial sample consists of about 20 million person-quarter observations or about 4 million unique people.

An additional advantage of the ENOE is its ability to track the characteristics of migrants. In each wave, interviewed household members report any new or absent members, as well as their broad origin/destination or reason for arrival/departure. Following Paredes and Mera-Ceballos (2012), we identify migrants by tracking changes in household rosters. An international migrant is someone who was present in quarter $t$ but marked as absent and in 'another country' in quarter $t+1$. Migrants can be present at most in four consecutive quarters, and require at least one household member to remain in the sample. Non-migrants are those who are never absent during their participation in the ENOE (up to five consecutive interviews). Since households can migrate at once, we identify and remove these observations from our analysis. In addition, we also identify non-migrants who live with migrants, and internal migrants, which we analyze separately as robustness checks. Appendix B.1 contains more information about whole-household migrants and the types of migrant categories. We create these categories because we observe people during multiple periods, but this does not necessarily imply that people are self-conscious of belonging in any of these categories at any given time.

For our purposes, the ENOE asks an important question on making preparations to cross the border. Specifically, the ENOE asks those who are not employed "Have you tried to look for a job in another country or make preparations to cross the border?"[5] For those who are employed, the survey restricts this question to the last quarter. The answers to this question are both different and more time and action-specific than questions on intentions used in other surveys (Carling & Schewel, 2018).[6] Specifically, they are informative about engaging in plans or preparations to migrate. This question is asked in every interview, so we can

[4]We limit the analysis to avoid the COVID-19 pandemic, which radically limited mobility worldwide.

[5]In Spanish: *"¿...ha tratado de buscar trabajo en otro país o hacer preparativos para cruzar la frontera?"*

[6]We include a longer discussion of these differences and data scope in Appendix B.4.

identify the time until respondents migrate (or leave the sample) and multiple interviews of preparing to migrate.

One advantage of the ENOE is that being a survey at the origin, there is no repercussion or fear to answer even when migrants plan to move without documents. Ibarraran and Lubotsky (2007) highlight that there may be an important under count of Mexican migrants in United States data sources because of fear of their legal status being visible to the government. The ENOE response rate does not suffer from this fear. However, this feature is a limitation for our analysis as people may prepare for longer or shorter depending on whether they will migrate with visas, residence permits or without. Therefore, our analysis cannot separate how preparing to migrate may vary for by the type of document to migrate.

We use two formats of the ENOE: a panel of respondents and a collapsed data frame with the last observed characteristics of the respondent. We restrict the analytical sample to observations between 2005 and the fourth quarter of 2019, and to people aged 12 years and older. The latter restriction is because the employment and preparation questions are asked only to those 12 years and older. We describe the subset of variables used in this analysis (Table B.2) and include descriptive statistics (Table B.3) in the appendix.

### 2.3.1 Analytical approach

As described above, we address three research questions in this paper, each of which pursues its own specific analytical strategy. For the first two questions, we use the collapsed ENOE dataset, where each observation corresponds to the data from the last surveyed quarter. For our third question, we exploit the panel structure of the data. All estimations are computed without using household weights.

We first ask about the extent to which preparations are linked to actual migration. To do this, we estimate the following logistic regressions where the outcome equals 1 if the person is a migrant and 0 otherwise.

$$Pr(migrant_i = 1) = logit^{-1}(\mathbf{X}\boldsymbol{\beta}) \tag{2.1}$$

$$Pr(migrant_i = 1) = logit^{-1}(\mathbf{X}\boldsymbol{\beta} + \alpha_i preparing_i) \tag{2.2}$$

The independent variables in $\mathbf{X}$ are sex, age, educational attainment, marital status, kinship, employment status, region of residence, income quartile, household age composition, year and quarter of survey, and a range of standardized macroeconomic variables.[7] We chose these characteristics as they have been important predictors in research on migration aspirations (Section 2.2) and abilities. From these models, we compare the stability of coefficients in $\boldsymbol{\beta}$, we interpret $\alpha$, the odds ratio associated with preparing to migrate, and we discuss the gain from including preparing to migrate as a predictor of actual migration.[8] We complement this analysis with descriptive tabulations and corresponding tests for differences in proportions.

[7] Respectively: wage differential between Mexico and the United States, state-employment rates in Mexico, overall unemployment rates in the United States, shortest distance from the municipality centroid to a United States-Mexico border point of entry, remittances received by states in Mexico.

[8] Appendix B.5 contains a discussion of an alternative way of evaluating the fit of the model when including preparing to migrate in the model.

In our second analysis, we predict migration preparations. We evaluate the characteristics of those who do and do not prepare, comparing how they differ. We estimate logistic regressions where the outcome is 1 if a person ever reported preparing to migrate, and 0 otherwise. In these models, we use the same characteristics as in the previous models, and we interpret the odds ratios for each variable. We estimate equation (3) for non-migrants and international migrants to understand if selection into preparations varies by migration outcome. These regressions are equivalent to the first-stage estimates described in Carling and Schewel (2018).

$$Pr(preparing_i = 1) = logit^{-1}(\mathbf{X}\boldsymbol{\beta}) \tag{2.3}$$

Finally, we estimate event studies to analyze how employment outcomes may change around migration preparations. We focus on employment-related outcomes because (i) they are not fixed characteristics, (ii) the preparation questions we use are framed around employment, and (iii) it is likely that employment and mobility outcomes move concurrently (De Jong, 2000; Kandel & Massey, 2002; Kley, 2011). Therefore, dynamically understanding the employment context may be crucial for situating preparations. We estimate the following regression where the outcomes of interest, $y_{it}$, are: being employed, weekly hours worked, the logarithm of real monthly income, and the probability of working in the informal labor market.

$$y_{it} = \sum_{\tau=-4}^{-2} \gamma_\tau D_\tau + \sum_{\tau=0}^{4} \gamma_\tau D_\tau + \alpha_i + \delta_t + \epsilon_{it} \tag{2.4}$$

As is customary with panel data estimations, we include person ($\alpha_i$) and year-quarter ($\delta_t$) fixed effects to account for the time-specific and unchanging characteristics of individuals. $D_\tau$ represents a dummy equal to 1 when the observation is $\tau$ quarters away from the quarter when preparations were first reported. For instance, $D_{\tau=0}$ is equal to 1 in the quarter when people report preparing to migrate (the quarter of the event is indexed to 0). In the next period, $D_{\tau=0}$ is equal to 0 but $D_{\tau=1}$ is 1. In this way, the event study is composed of dummies that are leads and lags around the event (i.e. the quarter when preparations are first reported). The omitted period, $\tau$ = -1, makes coefficients comparable to the period before preparations were reported. A positive $\gamma_{\tau\geq 0}$ means that the outcome at time $\tau$ is $\gamma_{\tau\geq 0}$ larger than in $\tau$ = -1. We restrict the sample to people who were continuously employed during all quarters for all outcomes, except for the probability of being employed. This ensures that changes in these outcomes are not due to being unemployed or leaving the labor force.

We include several robustness checks to understand heterogeneity within our sample. First, we consider differences across the duration of preparations to account for selection into short-term (one quarter preparing) and long-term (two or more quarters) patterns. Next, we review heterogeneity within international migrants by their reason for migration. Then, we compare non-migrants who live in the same household as another migrant to those who do not, and international migrants to internal migrants. We use these comparison groups since being exposed to migrants may make migration more attainable, and because existing research has noted that people may move internally before moving internationally (King & Skeldon, 2010). Two final notes before we move to the results are in order. First, despite the panel format of the data, we refrain from interpreting the results as causal estimates, but rather as associations because of omitted variable bias. Second, throughout the paper, we will refer to the quarter when preparations were first reported as the event.

## 2.4 Results

### 2.4.1 Are preparations linked to migration, and how long do they last?

We first present the prevalence of preparations within our sample (Table 2.1). This table shows that preparing to migrate is a fairly rare event since only a little over 13 thousand people stated that they have, at some point within the survey waves, prepared to migrate. Importantly, Table 2.1 also suggests that: i) most people who migrate did not substantially prepare beforehand (95.9% of those who migrate), and ii) not everyone who prepares ends up migrating (94.7% of those who prepare do not migrate). In terms of the frequency of the preparations, Figure 2.2 shows that conditional on preparing at least once, many non-migrants may spend multiple quarters preparing. But, in general, migrants who report preparing tend to leave a quarter later. This suggests that if, and whenever, there is a stage of preparations before migration, this period is fairly circumscribed in time.

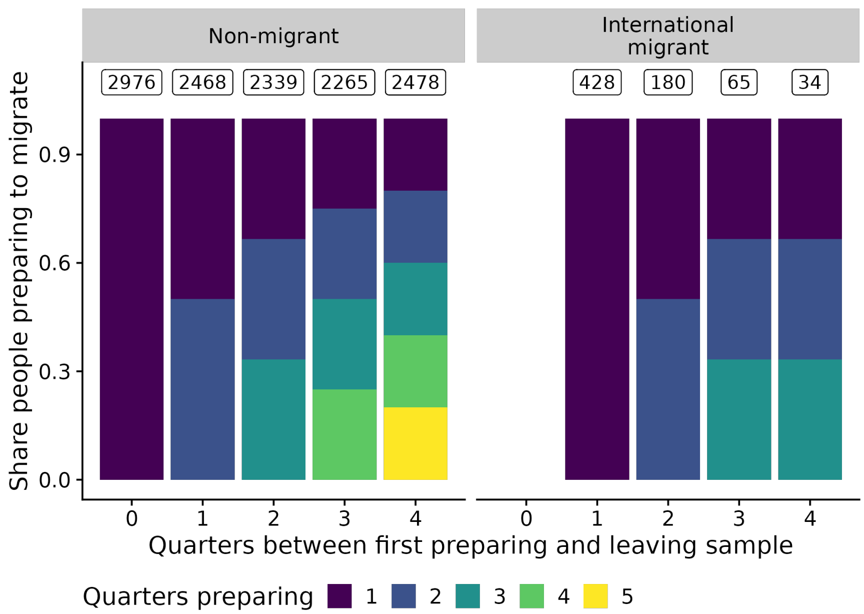
**Table 2.1:** Composition of respondents by preparations and migration categories

| Prepares? | Non-migrant | International Migrant | Total |
|---|---|---|---|
| No | 3,229,657 | 16,658 | 3,246,315 |
| | 99.6% | 95.9% | 99.6% |
| Yes | 12,526 | 707 | 13,233 |
| | 0.4% | 4.1% | 0.4% |
| Total | 3,242,183 | 17,365 | 3,259,548 |
| | 99.5% | 0.5% | |

Note: The shares are statistically different (p-value¡0.001) based on a chi-squared test for all pairs within a row. From here onward, Non-migrant omits people who have migrant ties and those who may have migrated as a household.

The previous results highlight the mismatch between preparing to migrate and actually migrating, suggesting that not everyone who prepares will migrate. Also important, not everyone who migrates, goes through a long period of preparations. We now turn to understand how strong the link between preparing and migrating is. Table 2.2 shows the association between preparing to migrate and actual migration. When we do not include covariates, column (1) shows that those who prepare to migrate are 10 times as likely to migrate as those who do not. When controls are added, the odds ratio decreases to 4.353 (Appendix B.5 shows the full regression results.). Despite the large odds ratio, the ROC analysis in Appendix B.5, which is informative of the ability to predict migrants, indicates that preparing to migrate helps only marginally to predict actual migration. This is likely because preparing to migrate is correlated with other characteristics in the model, as we will see in the next section. Together, these results suggest that the link between preparing to migrate and actually migrating is strong, but should not be considered as the sole predictor of migration.

**Figure 2.2:** Frequency and duration of preparing to migrate




Note: Numbers at top of bars show the total number of people preparing to migrate at each period.

### 2.4.2 Who prepares to migrate?

In this section, we analyze the determinants of preparing to migrate to deepen our understanding of selection into this pre-migration step. Table 2.3 shows the odds ratio from estimating logistic regression (3) above. We also report descriptive statistics in Appendix B.3, which show that people who claim to engage in preparations to migrate are different from those who do not prepare, regardless of their migration status.

The odds ratios of the categorical variables in Table 2.3 that are less than 1 and statistically significant suggest that the reference group is more likely to prepare to migrate than the coefficient in question. Therefore, we find that: i) being a man; ii) previously residing in historically migrant sending regions (with the exception of international migrants previously living in the northern region); iii) living in rural areas; iv) not having a partner; and v) being the household head; are all associated with higher odds of preparing to migrate, regardless

**Table 2.2:** Relationship between preparing and actual international migration

| | *Dependent variable:* | |
|---|---|---|
| | International migrant (0/1) | |
| | (1) | (2) |
| Preparations=1 | 10.785$^{***}$ | 4.353$^{***}$ |
| | (9.986,11.647) | (4.003,4.734) |
| Covariates | No | Yes |
| Observations | 3,843,707 | 3,843,679 |
| Log Likelihood | -110,077.800 | -94,798.830 |
| Akaike Inf. Crit. | 220,159.600 | 189,701.700 |

Note: Appendix E contains the full table with odds ratios for each variable. Stars show levels of significance: $^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ < 0.01.

of the subsample.[9]

We also find two interesting gradients in education and income. First, people with less than a high school education are less likely to prepare, but at very high educational levels (i.e., graduate degrees, and at the college level for non-migrants) people are more likely to prepare. Next, the odds of preparing to migrate are higher for incomes above the median[10] but are lower for those at the top of the income distribution. Additionally, we find that other characteristics are also associated with higher odds of preparing to migrate, namely being born in the United States (except for realized international migrants), being unemployed, and living in a household that receives remittances.

In terms of the continuous variables, we see that the odds of preparing to migrate increase with age. However, this happens at decreasing rates. Larger shares of households with children or individuals older than 65 years of age are not associated with higher odds of preparing to migrate. Finally, a one standard deviation increase in the wage differential or the employment rate in Mexico decreases the odds of preparing to migrate. Large distances to the border are associated with lower odds of preparing to migrate for non-migrants.

Interestingly, despite having distinct migration outcomes, non-migrants and international migrants have similar patterns in terms of their determinants of preparing to migrate. That is, columns (1) and (2) of Table 2.3 are qualitatively similar. Therefore, there is a general profile of people who prepare to migrate (highly educated, lower income, men, household heads, unemployed), as compared to those who do not.

[9] Average marginal effects show similar results. Results available upon request.

[10] Since more than 50% of the population has 0 income, the income range for Q3 is very low. Our reference group are those with no income (either because they are out of the labor force or they did not receive any income).

Another interesting result arises when we contrast these determinants to those of actual migration. In Table 2.3, we show estimates both for our preparations regression (column 3) and for our migration regression (column 4) in a sample that includes non-migrant and international migrants. We find key differences in higher education, having a partner, and being someone other than the household head. For instance, the odds of migrating are low at any educational level, relative to high school; but the odds of preparing are higher for those with graduate degrees. Having a partner is associated with lower odds of preparing, but with higher odds of migrating. Being the household head is associated with higher odds of preparing, but with lower odds of migrating. In this sense, these results suggest that household heads may instead be preparing for others to migrate within the household. There are some similarities too, though: living in a historically migrant-sending state and receiving remittances are always associated with higher odds of preparing and migrating.

The results from this section highlight how preparing to migrate may be similar for future non-migrants and actual migrants, but also that the determinants of preparing do not line up exactly with those of migrating. Next, we analyze employment patterns; we hope this may help explain differences in contexts leading to preparations.

**Table 2.3:** Odds ratio from logistic regression models on preparing to migrate and actual international migration.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| Outcome | Ever preparing to migrate (0/1) | | | Being an international migrant (0/1) |
| Sample | Non migrants | International migrants | Full Sample | Full Sample |
| | (1) | (2) | (3) | (4) |
| Intercept | 0.001*** | 0.012*** | 0.001*** | 0.003*** |
| | (0.001,0.002) | (0.002,0.073) | (0.001,0.002) | (0.002,0.004) |
| Female=1 | 0.438*** | 0.333*** | 0.414*** | 0.330*** |
| | (0.416,0.461) | (0.244,0.455) | (0.394,0.435) | (0.317,0.344) |
| Age | 1.162*** | 1.093*** | 1.165*** | 1.125*** |
| | (1.151,1.173) | (1.045,1.144) | (1.155,1.176) | (1.118,1.132) |
| Age squared | 0.998*** | 0.999*** | 0.998*** | 0.998*** |
| | (0.998,0.998) | (0.998,0.999) | (0.998,0.998) | (0.998,0.999) |
| **Region in Mexico (ref: Historic migrant-sending states)** | | | | |
| North | 0.988 | 1.497*** | 0.958 | 0.445*** |
| | (0.936,1.042) | (1.137,1.970) | (0.909,1.010) | (0.423,0.468) |
| Center | 0.854*** | 0.791** | 0.832*** | 0.606*** |
| | (0.814,0.896) | (0.642,0.974) | (0.794,0.872) | (0.582,0.630) |
| Southeast | 0.617*** | 0.533*** | 0.592*** | 0.379*** |
| | (0.576,0.660) | (0.372,0.763) | (0.554,0.633) | (0.355,0.403) |
| **Place of birth (ref: Mexico)** | | | | |

| | | | | |
|---|---|---|---|---|
| USA | 7.421*** | 1.010 | 6.871*** | 12.904*** |
| | (6.497,8.477) | (0.631,1.616) | (6.046,7.809) | (11.919,13.969) |
| Rest of the world | 1.436** | 0.343* | 1.426** | 12.334*** |
| | (1.082,1.907) | (0.106,1.110) | (1.083,1.878) | (10.948,13.896) |
| **Urban=1** | 0.668*** | 0.654*** | 0.644*** | 0.427*** |
| | (0.644,0.693) | (0.543,0.787) | (0.621,0.668) | (0.414,0.441) |
| **Current education (ref: High school)** | | | | |
| None | 0.721*** | 0.554* | 0.705*** | 0.683*** |
| | (0.634,0.820) | (0.289,1.061) | (0.621,0.800) | (0.618,0.755) |
| Elementary | 0.824*** | 0.824 | 0.832*** | 0.988 |
| | (0.778,0.873) | (0.646,1.052) | (0.786,0.880) | (0.942,1.036) |
| Middle school | 0.923*** | 0.975 | 0.933*** | 1.037 |
| | (0.877,0.972) | (0.780,1.218) | (0.887,0.980) | (0.992,1.084) |
| Trade school | 0.927 | 1.099 | 0.925* | 0.630*** |
| | (0.845,1.018) | (0.650,1.857) | (0.844,1.014) | (0.570,0.697) |
| College | 1.076** | 0.766 | 1.053* | 0.748*** |
| | (1.017,1.137) | (0.548,1.071) | (0.997,1.113) | (0.707,0.790) |
| Graduate studies | 1.217*** | 3.420*** | 1.233*** | 0.691*** |
| | (1.057,1.400) | (1.628,7.185) | (1.075,1.415) | (0.577,0.828) |
| **Labor force status (ref: Employed)** | | | | |
| Unemployed | 3.730*** | 5.626*** | 3.892*** | 1.694*** |
| | (3.525,3.947) | (4.560,6.941) | (3.688,4.108) | (1.587,1.808) |
| Available | 0.757*** | 0.502** | 0.724*** | 0.704*** |
| | (0.682,0.841) | (0.284,0.891) | (0.653,0.802) | (0.656,0.757) |
| Unavailable | 0.398*** | 0.778* | 0.396*** | 0.608*** |
| | (0.369,0.429) | (0.580,1.044) | (0.368,0.426) | (0.580,0.637) |
| **Has partner=1** | 0.909*** | 1.121 | 0.934** | 1.832*** |
| | (0.860,0.960) | (0.849,1.480) | (0.885,0.986) | (1.745,1.922) |
| **Relationship to household head (ref: head of household)** | | | | |
| Spouse/Partner | 0.577*** | 0.858 | 0.593*** | 0.730*** |
| | (0.535,0.621) | (0.631,1.167) | (0.551,0.637) | (0.683,0.780) |
| Child | 0.723*** | 0.649*** | 0.742*** | 3.003*** |
| | (0.679,0.769) | (0.483,0.871) | (0.699,0.788) | (2.842,3.173) |
| Grandchild | 0.539*** | 0.669 | 0.559*** | 2.658*** |
| | (0.453,0.640) | (0.360,1.241) | (0.474,0.660) | (2.392,2.953) |
| Daughter/Son in-law | 0.661*** | 0.559** | 0.670*** | 2.232*** |
| | (0.579,0.755) | (0.344,0.910) | (0.589,0.761) | (2.051,2.430) |
| Other | 0.583*** | 0.582** | 0.604*** | 4.183*** |
| | (0.521,0.652) | (0.369,0.917) | (0.542,0.673) | (3.906,4.481) |
| **Share of household members** | | | | |
| Children | 0.737*** | 0.827 | 0.737*** | 0.593*** |
| | (0.669,0.812) | (0.537,1.275) | (0.671,0.809) | (0.544,0.646) |
| Elderly (> 65) | 0.817 | 0.566 | 0.752** | 0.359*** |
| | (0.627,1.064) | (0.146,2.194) | (0.580,0.975) | (0.295,0.435) |
| **Income quartile (ref: lowest 2 quartile/ 0 income)** | | | | |

| | | | | |
|---|---|---|---|---|
| Income Q3 | 1.428*** | 1.120 | 1.350*** | 0.574*** |
| | (1.355,1.504) | (0.920,1.363) | (1.284,1.419) | (0.550,0.600) |
| Income Q4 | 0.789*** | 0.825 | 0.749*** | 0.478*** |
| | (0.744,0.838) | (0.653,1.042) | (0.707,0.793) | (0.455,0.502) |
| **Remittances** | | | | |
| Household receives remittances=1 | 1.512*** | 1.316*** | 1.654*** | 3.841*** |
| | (1.434,1.594) | (1.114,1.554) | (1.574,1.738) | (3.711,3.974) |
| Real remittances received (state) | 1.096*** | 0.943 | 1.095*** | 1.131*** |
| | (1.068,1.124) | (0.835,1.064) | (1.068,1.122) | (1.106,1.157) |
| **Macroeconomic trends** | | | | |
| US-Mex wage difference | 0.756* | 0.836 | 0.759* | 1.055 |
| | (0.563,1.016) | (0.207,3.381) | (0.569,1.013) | (0.812,1.370) |
| Unemployment rate (US) | 0.953 | 0.983 | 0.955 | 0.979 |
| | (0.848,1.071) | (0.564,1.712) | (0.852,1.071) | (0.884,1.084) |
| Employment rate (Mex) | 0.922*** | 0.914 | 0.923*** | 0.982 |
| | (0.897,0.947) | (0.805,1.038) | (0.899,0.947) | (0.959,1.007) |
| Distance to border | 0.952*** | 1.243*** | 0.950*** | 0.772*** |
| | (0.925,0.981) | (1.061,1.456) | (0.923,0.978) | (0.751,0.794) |
| Year | Yes | Yes | Yes | Yes |
| Quarter | Yes | Yes | Yes | Yes |
| Observations | 3,242,182 | 17,338 | 3,259,520 | 3,259,520 |
| Log Likelihood | -74,533.320 | -2,610.180 | -77,723.070 | -91,606.430 |
| Akaike Inf. Crit. | 149,168.600 | 5,322.359 | 155,548.100 | 183,314.900 |

Note: The level of significance from p-values is $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Regressions also include year and quarter variables (results available upon request). Full sample refers to non-migrants and international migrants.

### 2.4.3 How do employment outcomes vary before and after preparing to migrate?

In this section, we focus on the relationship between migration preparations and employment outcomes. We focus on four outcomes: i) the probability of being employed; and, for people who are continuously employed, ii) weekly hours worked, iii) the logarithm of real monthly income, and iv) the probability of entering the informal labor market.[11] All results from these event studies are interpreted relative to the period before people prepare ($\tau$ = -1). Standard errors clustered at the individual level.

[11]Full table of results available in Appendix B.6.

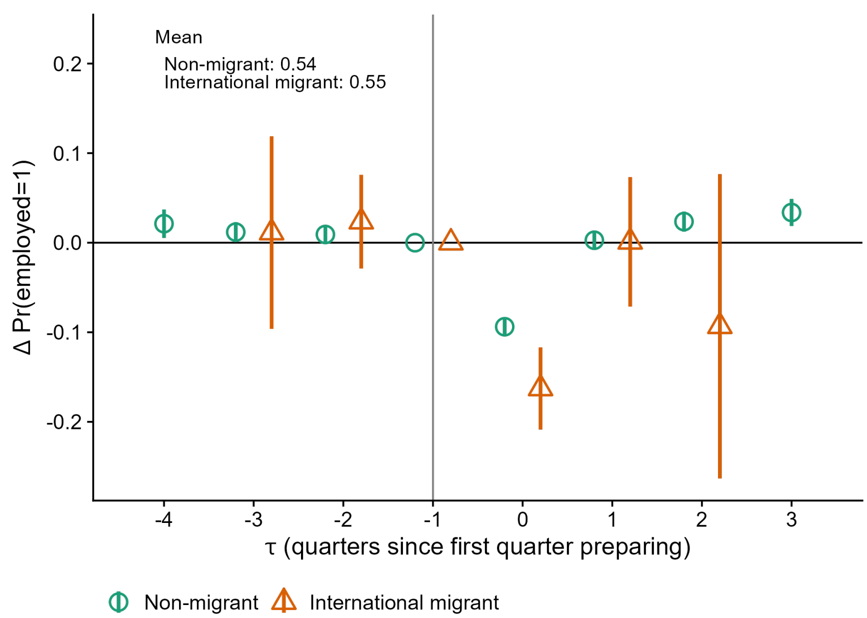
First, we analyze patterns in employment. In Figure 2.3, the coefficient at $\tau = 0$ is negative and departs from the past trend of positive (for non-migrants) or statistically insignificant (for international migrants) coefficients. This suggests that non-migrants are 9.4 percentage points (p.p.), and international migrants are 16.3 p.p., less likely to be employed during the quarter of the event. After the event, those who remain in Mexico are more likely to be employed.

Within people who have been continuously employed, we see differences between the non-migrant and the international migrant experience. Figure 2.4 shows a dip in hours worked by non-migrants in the period of the event. This dip corresponds to 2.6 fewer hours worked per week (or 5% of the mean). International migrants also experience a (non-statistically significant) dip. However, they experience a later change: two quarters after the event, they work 7.8 hours more.

Despite the decrease in hours worked at the time of the event, Figure 2.5 shows a growth in income of about 25% for non-migrants. Non-migrants who report preparing to migrate, experience a decrease in real income of 23% three periods before the event. This is almost entirely offset by the increase experienced during the quarter of the event. International migrants who prepare do not experience any statistically significant changes in their logarithm of income.

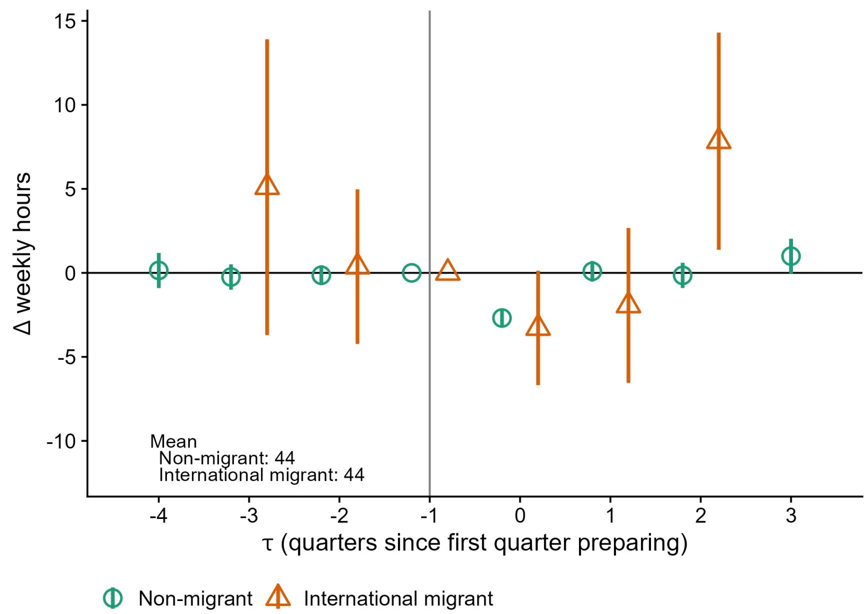
The informal sector is an alternative market where employees are typically not offered benefits, such as health insurance, or formally pay taxes. Jobs in this sector are often unstable and based on one's employment. According to Figure 2.6, international migrants who prepare are 8 p.p. more likely to work in the informal sector at the time of preparing. This transfer to an informal sector job is not observed for non-migrants.

**Figure 2.3:** Event study results for the probability of being employed



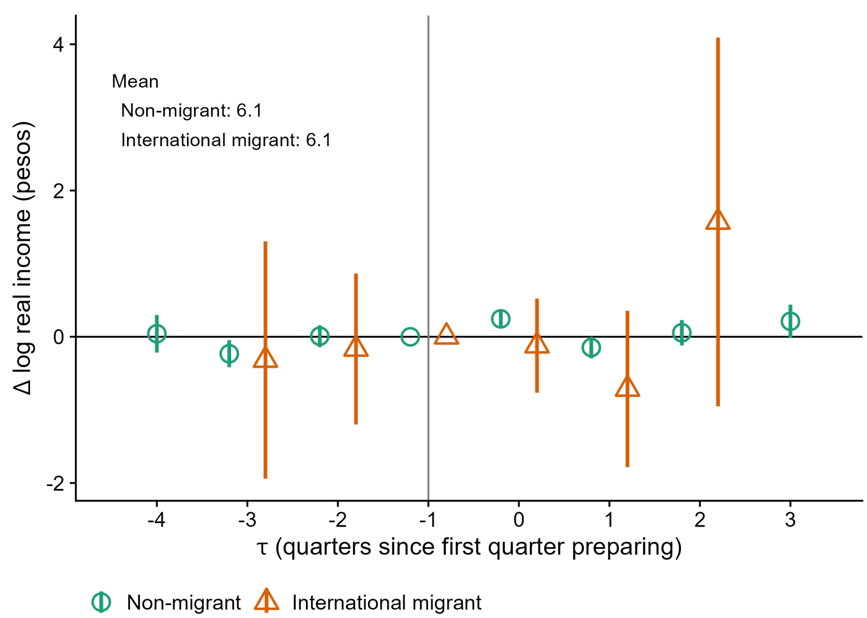

Note: Error bars represent 95% confidence intervals.

**Figure 2.4:** Event study results for weekly hours worked



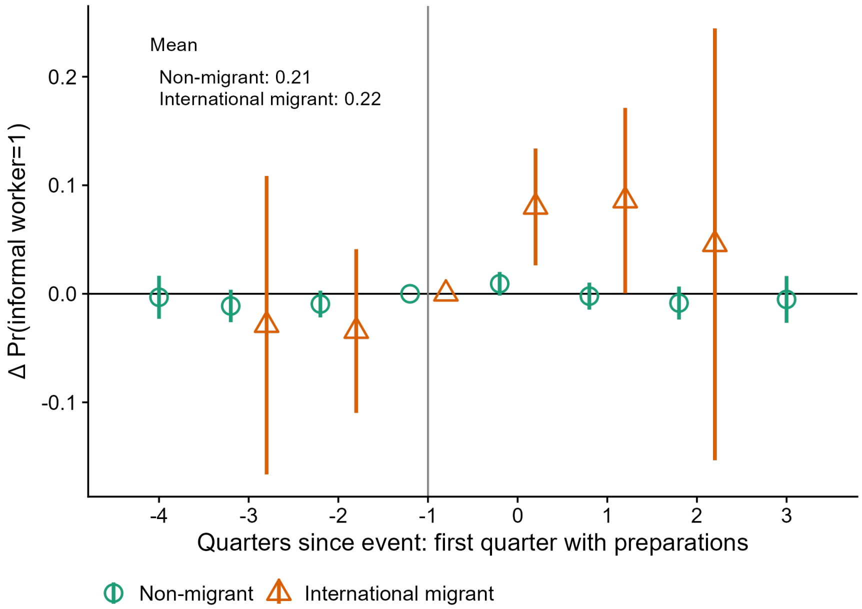

Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

**Figure 2.5:** Event study results for logarithm of real monthly income (in pesos)




Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

**Figure 2.6:** Event study results for the probability of working in the informal sector




Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

What might these changes signal? First, preparing to migrate is reported in periods of sudden unemployment. While some people migrate internationally and realize their preparations, those who remain in Mexico also experience positive employment outcomes following their preparations. In this sense, migration preparations, alongside the factors correlated to both employment behaviors and preparations, may still help employment outcomes, even when preparations are not realized. All the above factors are important clues for how international migration ambitions may be eventually replaced with employment within Mexico.

Second, conditional on always being employed, those who fulfill their preparations to migrate internationally experience no income variation. However, they work more hours and are more likely to work in the informal sector, both when they begin preparing and after the event of signaling preparations. Non-migrants experience a decrease in income right before preparing. However, this is almost compensated by an increase in income in the quarter when they prepare to migrate. Interestingly, this increase in income is accompanied by a decrease in hours worked, which means that the increase in income comes from higher wages.

In this sense, international migrants differ substantially from non-migrants as they start preparing in more (relatively) prosperous times (i.e. with no change in income). This likely means that since they are already working, they must have alternative reasons to migrate. However, these migrants instead move to potentially more precarious jobs in the informal sector, and even increase the amount of hours they work. Conversely, despite a slight income fluctuation, non-migrants tend to recover after engaging in preparations and are even likely to work fewer hours after the event.

### 2.4.4 Heterogeneity

In this section, we explore possible sources of heterogeneity inputted into our data, particularly those related to the duration of the preparation phase and the reasons for migration. We also explore how preparations may vary for: i) internal migrants, and ii) non-migrants with ties to migrants within their households.

First, we investigate if people who spend less time preparing (one quarter) have different outcomes from those who prepare for longer (two or more quarters). Table B.8 in the Appendix shows that, for most variables, the odds ratios do not vary substantially across duration of preparations to migrate. We continue to see the same variables being more predictive of preparing to migrate, as well as the same gradients of change uncovered above in terms of education and income. However, in what pertains to employment outcomes, longer periods of preparation by international migrants are associated with large and sustained decreases in the probabilities of being employed. Other than these differences, the results across different lengths of preparation do not differ substantially from our main results.

Another possible form of heterogeneity stems from the different reasons for migration. For people who are absent, the ENOE collects the main reason for migration, as reported by the remaining household members. Appendix Table B.9 estimates the odds ratios of preparing to migrate for current international migrants, per reason for migration. We find that the odds ratios are overall stable to the inclusion of this variable, and that people who migrate for work have the highest odds of preparing for migration, followed by those migrating to pursue education. Given these results, we estimate the odds of preparing to migrate for international migrants who leave for work and due to other reasons separately. We find that many of the takeaways from the full migrant sample persist. But we also discover that they are likely driven by the people who migrate for work, since the odds ratios for the people who migrate for other reasons are less precisely estimated. One important difference is that the large odds ratio for people with graduate degrees is likely driven by people who migrated for reasons other than work. As for the employment outcomes, our main results resemble those of the work migration subsample. International migrants who leave for reasons other than work face both a decrease in income and an increase in hours worked before the event. After the event they are substantially more likely to be working informally. Based on these results, we can state that international migrants who prepare and actually migrate for non-work reasons are subject to more economic hardship than those who migrate for work.

Finally, we include a comparison of the results attained in our main analyses to those obtained for internal migrants and for non-migrants living in households with other migrants. Our goal here is to understand if preparations to migrate internationally can be substituted by internal migration, on the one hand; and if there is something about previous close contact with migrants (and migration) that can influence the preparations of other household members. Starting with the latter, our results show that non-migrants with and without migrant ties have similar outcomes, including in terms of employment (Appendix B.9). Likewise, internal migrants who had prepared to migrate internationally are also similar to international migrants who had prepared. However, interestingly, internal migrants behave like non-migrants in terms of their probability of being employed, hours worked, and in their probability of working in the informal sector. Conversely, they resemble international migrants in what pertains to changes in income. This highlights that internal migrants who prepare to migrate internationally may end up opting for internal migration as a replacement strategy or as a stepwise migration project.

## 2.5 Discussion and conclusions

Analyzing preparations to migrate is informative of migration as a decision-making process. Yet, especially when compared to other phases, this is an understudied step in the migration decision-making process. Instead, most of the existing research has focused on the preceding stage of aspirations to migrate or on actual migration capabilities. Using rich quantitative data from Mexico, we can piece out the relevance of the preparatory phase within the migration-decision process. Specifically, we look at: i) how important preparations are for migration, ii) the temporality of preparations, iii) how the preparations evidence self-selective patterns, and iv) whether employment outcomes vary along with migration preparations. All around, we provide an all-encompassing analysis of what has been identified as a key stage of the migration decision-making process (Kley, 2011).

First, we find that the expected sequence of preparing to migrate and actually migrating is a relatively rare event. Our results highlight that preparing to migrate (for at least as much as a quarter) is not a necessary, nor even a particularly frequent, condition for actual migration, not even in the context of a historically migrant-sending country such as Mexico. Conversely, people do seem to be able to migrate despite not spending a long and consistent time preparing. In addition, our findings highlight that, whenever they do occur, migration preparations tend to not last more than one quarter.

Next, we examine the characteristics of those who claim to prepare to migrate. We find that people embedded in migrant networks, either through their region of residence or by receiving remittances, are more likely to prepare to migrate. These findings are consistent for those who prepare but do not migrate and for those who, having prepared, end up migrating. This may reflect the fact that migration in Mexico is quite socially integrated, as highlighted by previous works on mechanisms of cumulative causation and migrant networks (Curran & Rivero-Fuentes, 2003; Massey & Espinosa, 1997). We are, however, at least to our knowledge, the first to quantitatively document how migration networks and culture of migration affect the odds of engaging in migration preparations. This raises important questions about how selection into preparations (and larger barriers to preparing) can limit migration, thereby furthering the gap between aspirations and capabilities. Additionally, to the extent that preparing enhances the migrant experience, it can also become a form of inequality, relative to those who do not prepare, potentially leading to differing outcomes also in the destination.

We also document traits associated with preparing to migrate that are not typical predictors of actual migration from Mexico. For instance, we find a strong education gradient, whereby people with graduate degrees have higher odds of preparing to migrate. The latter is consistent with the findings of Creighton (2013) for the case of migration aspirations in Mexico. Highly educated individuals spend a longer time in the pre-migration phase. This may reveal the privilege of choosing when to migrate, higher returns on human capital, more time spent performing a risk-analysis of migration, or point to limitations in the job market prospects in the destination for highly qualified individuals. Another important difference between preparing to migrate and actually migrating is that household heads are more likely to prepare than anyone else in the household. However, they are less likely to migrate. This may be a sign that preparations to migrate may be transferred to other household members. If this is true, then the already strong link between preparing and migrating may be strengthened more by the spreading of preparations. Further delving into these effects could be a productive extension of this project.

Finally, we consider whether preparations can affect structural, particularly employment outcomes, much like aspirations have been found to do for school outcomes (Kandel & Massey, 2002). Our research allows us to address some of the shortcomings of cross-sectional analyses, by considering variations before and after preparing to migrate. In this regard, we find that preparations to migrate tend to occur in sudden periods of unemployment. However, if people remain in Mexico and do not materialize those preparations into actual migration, they usually tend to become employed again within half a year. This is promising evidence that reporting preparations (and their correlates) is related to positive changes in employment outcomes, even when these preparations are not fulfilled. Our event studies also suggest that those who prepare to migrate but have different migration outcomes have distinct labor market experiences, despite having similar determinants. Non-migrants begin preparing three quarters after their income decreases, while those who end up migrating internationally usually start preparing in periods without income changes. However, international migrants find themselves in more precarious situations after preparing, while their non-migrant counterparts improve their conditions. A surprising finding is that labor outcomes change in the quarters of the event, which suggests a sensitivity to preparing to migrate.

Taken together, these findings reflect that migrants and non-migrants have structural differences that allow them to respond and fulfill the link between preparations and actual migration. The New Economics of Labor Migration proposes that migration is a way to minimize risk and smooth income fluctuations (Massey et al., 1993). However, we see no link between the timing of preparations and changes in real incomes for future international migrants. This leads to questions about how social and economic shocks may affect the preparatory phase of migration. Preparing to migrate likely reflects a larger structure of advantages, which could moderate the effects of shocks, for instance, those related to violence in Mexico (see Aldeco Leo et al. (2022) and Massey et al. (2020)).

Beyond the theoretical implications of this work, we suggest future researchers should be cautious when analyzing preparations in the migration process. First, using preparations to migrate as a proxy for future migration abilities would overestimate total migration. As we uncovered, not everyone who prepares, actually migrates (and vice versa). Similarly, assuming that all migrants spend much time preparing would be erroneous. Second, researchers considering fielding longitudinal surveys on migration may consider including more frequent waves (less than a quarter), since we find that preparations do not last long, regardless of migration outcomes. Furthermore, we recommend that researchers include broad questions on migration preparations in their surveys, alongside questions on migration intentions and aspirations. This would be a useful addition to the types of questions categorized in Carling and Schewel (2018). Such questions should be broad enough to not allude singly to employment reasons, but ideally, specify reasons for the migration preparations underway.

Finally, where possible, we encourage researchers to adopt a longitudinal approach to analyze migration processes.

Despite its promise and the advances it inspires for the study of migration decision-making, our work does have some limitations. The ENOE has a narrow time frame (five quarters) which prevents analyzing longer-term changes in our outcomes of interest. For instance, applying for visas to the United States can be a long process in Mexico, possibly several quarters. Therefore, a respondent may not consider this as an ongoing process and they would appear as if they are not preparing to migrate. We might ironically run into the opposite concern, i.e. that the planning or preparatory phase is very short-lived in many cases, and thus not captured in the quarterly surveying we utilize. The fact that most of the respondents who prepare for migration and then migrate, only prepare for just one quarter hints strongly at this possibility. However, this is in itself interesting data on the (short) temporality of the planning stage. We encourage future analysis to continue exploring the long-run dynamics of migration preparations.

Another possible limitation is that our framework does not fully allow for establishing causal estimates regarding the effects of preparations. Still, our event studies do suggest that preparations are highly correlated with employment conditions. We are just not fully able to establish a sequence of events. Lastly, ensuing work could include analyses by gender, urban/rural divides, or focus more thoroughly on possible geographic variations in terms of outcomes. Additionally, future studies might also use a machine learning approach to better assess the predictive power of migration preparations.

Still, we want to emphasize that, to our knowledge, this study provides the most encompassing survey of migration preparations to date, thus contributing to the broader understanding of migration as a stepwise decision-making process. Our work provides important clarity and knowledge on a purportedly important phase of migration decision-making, i.e. the preparatory phase, and by that on the drivers and constraints of migration. Our results address important (mis)conceptions about the expectation and temporalities of migration preparations, highlight the existence of self-selective mechanisms into preparations, and establish important links between engaging in preparations, actual migration, and employment behaviors and outcomes. We believe that these results provide contributions to migration research, as well as to the study of the nexus between international mobility and individual and community development. Our study collectively speaks to the non-trivial nature of preparing to migrate, highlights the importance of focusing on migration preparations, and will thus hopefully become a benchmark for future analyses of migration preparations and decisions in other regional and national contexts.

# Chapter 3

# An Illusion or a Subtle Trend? Revisiting the Feminization of Emigration from Mexico

## 3.1 Introduction

How does our understanding of emigration change when we consider women's (im)mobility? In the 1990s, policymakers noted the high participation of men in international emigration and questioned whether this reflected underlying sex-specific inequalities (United Nations International Research and Training Institute for the Advancement of Women (INSTRAW), 1994). The bias towards male migrants was partially due to data limitations and a lack of theory that incorporated sex as a determinant of emigration. However, with advances in data and continued interest in female emigration, we know that in the year 2000, 47.5% of international migrants worldwide were female, and this share increased to 48% by 2024 (McAuliffe & Oucho, 2024). More than half of migrants are male, but the gap is shrinking. Moreover, the small increase of 0.5% represents a large volume of female international migrants: from 71.25 million in 2000 to 134.88 million by 2024 (McAuliffe & Oucho, 2024). Additionally, there is substantial geographic variation in the share female, which begs the question: what makes female and male migrants different?

Understanding the differences between female and male migrants is not trivial, as emigration operates within the larger structure of society; it is also affected by the expectations and limitations that a specific sex is subject to. For instance, demand for workers worldwide can directly target a particular sex through job descriptions and indirectly through skills that are present in a sex-specific labor pool (Oishi, 2005). Accessing these job opportunities is also limited by the culture, context, and expectations of men and women. In addition, the ability to migrate is also determined by individual, household, and contextual factors, which can vary by sex. Therefore, emigration can exacerbate existing inequalities between men and women.

The Mexico-United States (U.S.) is the largest emigration corridor but the emigrant flows have been dominated by men. However, the decline in emigration streams from Mexico and the increase in return migration show that this is a new era of Mexican migration (Giorguli-

Saucedo et al., 2016). The extent to which this era has also led to sex-specific patterns of emigration is unknown. In this chapter, I ask: What can we learn from any changes in the sex-composition of emigration from Mexico during the 21st century? As a historically migrant-sending country, it continues to be important to assess patterns of selection into emigration, in particular, if these differ between men and women. Since emigration has a transformative power on the migrant and the community of origin, any barriers to emigrate (such as those correlated to sex) are a form of inequality, one that limits human development. Female emigration has been understudied in quantitative research on Mexican migration and is often only considered relative to household emigration.

Using a range of data from Mexico, including the Mexican Labor Forces Survey, censuses, and demographic surveys, I document the sex-specific trends of emigration from Mexico from the year 2000 to 2020. I find that the share of emigrants who are female increased from 25% to 33% in 2020, which indicates that there is a change in who can migrate. However, the share aggregates trends in female and male emigrant counts, which hides the fact that male emigration has decreased while female emigration has remained stable. Therefore, the increase in the share of female emigrants is an illusion of the 'feminization' of emigration.

As emigration results from push and pull factors operating at different levels (individual, household, and aggregate), it is difficult to pinpoint the source of differences between male and female emigrants from only analyzing the counts of emigrants. A solution is to use decomposition analysis to separate the contribution of changes in the determinants of emigration and changes in the population composition. The results suggest that changes in the determinants of emigration explain the increases in the share female. Focusing on the sex of emigrants is important to bring awareness of the sex-specific constraints on emigrants from Mexico. These constraints become a source of inequalities that hinder the development of the female population.

By leveraging rich data, I provide an updated view of whether and how female emigration has changed. This chapter builds on the literature that questions the feminization of emigration in Mexico (Giorguli & Angoa, 2016; Lowell & Pederzini, 2012) by explaining the contribution in changes of the composition of migrants. To my knowledge, this is the first study to use a breadth of individual-level predictors to understand female emigration from Mexico and to try to decompose it into selection processes and population composition. To set up the analysis, I overview the determinants of female emigration and findings on the feminization of emigration in the next section. Following that, I outline the data I will use in section 3.3 and present trends on the share of female migrants in section 3.4. Section 3.5 maps the selection and composition effects on the feminization of emigration, which I discuss in section 3.6.

## 3.2 Feminization and female emigration in Mexico

There was an important push in the early 1990s to include women in the emigration analysis (Curran et al., 2006; Donato, 1993; Donato et al., 2006; Hondagneu-Sotelo, 2000; Kanaiaupuni, 2000; Pessar & Mahler, 2003). In addition, there are numerous critiques about the lack of a formal migration model for female emigration (Bircan & Yilmaz, 2022; Curran et al., 2006; Donato et al., 2006; Giorguli & Angoa, 2016). However, more recently there is a discussion about whether there is a 'feminization of emigration' (Giorguli & Angoa, 2016); whether it is a phenomenon of the last decades (Bircan & Yilmaz, 2022) or most importantly how to define it (Bircan & Yilmaz, 2022; Donato & Gabaccia, 2015). In their book, Donato and Gabaccia (2015) use the share of emigrants who are female to measure feminization. Specifically, they define categories based on the share female: "male-predominant migration as less than 47 percent female, gender-balanced migration as 47 to 53 percent female, and female-predominant migrations as greater than 53 percent female", and "heavily male predominant...as any migrant population that is less than 25 percent female" (Donato & Gabaccia, 2015, p.50-51). Based on these categories, feminization of emigration may be i) "any multiyear rise in the percentage female among migrants", ii) "any shift from one category to another (from heavily male to male-predominant, or from male-predominant to gender balanced)", and iii) "any increase in the proportion female that has demonstrable consequences for migrants, for their homelands, or for the new societies they enter" (Donato & Gabaccia, 2015, p.51-52). It is clear from the multiple definitions that female and male emigration must be assessed in different ways. In the rest of the paper, I use the first definition to mean the *process of feminization*. With the development of definitions and frameworks of 'feminization' and appropriate data, more research on female and male emigration is possible.

To understand feminization, we need to consider the determinants of female emigration. The earliest work on international female emigration from Mexico suggests that the characteristics of households affect the probability of female emigration. In the post-IRCA world, Donato (1993) explains that women migrated to reunite with their families but she stressed that "it is not clear whether the motivation underlying these moves is restricted only to family reunification". Subsequent work focused only on male emigration (Durand et al., 1996; Massey & Espinosa, 1997) because of data limitations that led to small sample sizes of female migrants.[1] Beyond female emigration, data and small sample sizes continue to be a reason why the experiences of subpopulations (i.e., children, Indigenous people, or sexual minorities) are not studied in quantitative research.[2]

In the early 2000s, more research would focus on female emigration and would find that, specifically in Mexico, gender plays an important role in social interaction and structure, ultimately shaping the decision to migrate (Pessar & Mahler, 2003). There are distinct emigration responses by gender to employment opportunities (Cerrutti & Massey, 2001), in the presence of migrant networks in the U.S. (Curran & Rivero-Fuentes, 2003; Davis & Winters, 2001) and due to social norms in Mexican communities (Kanaiaupuni, 2000; Massey et al., 2006). In particular, there is evidence that men migrated first and were then followed by their family (Cerrutti & Massey, 2001). Overall, female emigration in Mexico has been associated with social reasons, such as migrant networks or social capital, rather than economic emigration.

Discussions about feminization cannot omit the process of selection into emigration. Researchers debate whether people are more likely to migrate if they have high or lower incomes, and more or less formal education. In Mexico, income (Moraga, 2011) and education

[1]A prevalent source of data for research on Mexican emigration is the Mexican Migration Project, which has a sampling design that favors communities with high emigration rates. Since emigration rates from the past were mostly composed of men, then the sample is skewed to male emigration.

[2]There is a rich qualitative literature on female emigration but it is not nationally representative.

have been analyzed. There is conflicting evidence about whether selection is positive or negative (Chiquiar & Hanson, 2005; Feliciano, 2005; Rendall & Parker, 2014). When sex is added to the analysis, Rendall and Parker (2014) find that male migrants from Mexico are negatively selected (lower formal education) but after female migrants have a neutral selection in terms of education (similar to non migrants). Lowell and Pederzini (2012) focus on higher (tertiary education) and find that female emigration is higher than male emigration only for those with PhDs.

Beyond the sex of migrants, understanding the composition of migrant flows is important to gauge the possible demographic, social, and economic impacts at the destination and origins. For instance, selection into emigration also affects sending communities through household and family structures (Bertoli & Murard, 2020; Nobles, 2013), education (Antman, 2012), politics (Andrews, 2018), investment of remittances (Oishi, 2005) and redistribution of population within the country. Therefore, having a clear understanding of *who* constitutes emigration flows informs the potential impacts of emigration at the origin and destinations. This speaks to the literature on selection to migrate, which for Mexico has mostly focused on the male side (Chiquiar & Hanson, 2005; McKenzie & Rapoport, 2010; Moraga, 2011; Villarreal, 2014). Except for Kaestner and Malamud (2014) and of work on educational selectivity (Feliciano, 2008; Feliciano, 2005; Hamilton & Bylander, 2020; Lowell & Pederzini, 2012; Rendall & Parker, 2014), little is known about selection into emigration by female migrants, and much less about selection in the last 20 years.

Yet, the wave of research that looked at feminization of emigration has decreased in the last decade, mostly limited by the available data. Previous work on feminization of emigration in Mexico has documented trends in the share of female migrants in specific subset (i.e., the highly-educated (Lowell & Pederzini, 2012)) and the aggregate (Giorguli & Angoa, 2016) but have not explained how a combination of migrant characteristics can explain the trends. Here, I use a dataset with rich covariates to understand how the composition of migrants can explain the trend in the share of female migrants in Mexico.

Due to data limitations, I cannot make the distinction between 'sex' and 'gender', and I assume that reported sex is sex at birth. Therefore the results do not speak to gendered processes of emigration Bircan and Yilmaz (2022) and Donato et al. (2006). Moreover, this work only pertains to international emigration from Mexico, which I elaborate more on in the next section.

## 3.3 Data

To understand the differences between male and female migrants, I focus on demographic, social, and economic characteristics using a range of data. The primary data comes from the *Encuesta Nacional de Ocupación y Empleo* (ENOE), which is a nationally representative household survey that provides timely unemployment estimates. It has a panel structure where sampled households are followed for up to five quarters. I use all waves of the ENOE since 2005 and stop at the first quarter of 2020 to avoid the COVID-19 Pandemic. For more details on the ENOE, refer to Chapter One. Overall, the ENOE can be used to obtain characteristics of migrants, similar to other standard data, despite it not being a demographic survey. In addition to the ENOE, I also use the extended questionnaires of the

2000, 2010 and 2020 Censuses, and three waves of the *Encuesta Nacional de la Dinámica Demográfica* (ENADID). The ENADID is a cross-sectional survey that collects information on demographic trends on mortality, fertility, international migration, and internal mobility.

The Census and the ENADID ask household members about any international emigrants within the last five years. At the time of the interview, some migrants remain abroad while others have returned. The ENOE is different because migrant characteristics are reported directly by the respondent (who will become a migrant) before their departure. Therefore, there is less of a risk of recollection bias or misreporting by the family members. For this chapter, I use the collapsed ENOE, where the characteristics of each respondent correspond to their last interview. To complement the individual-level records from the ENOE, I rely on macroeconomic data, distances from municipalities to the U.S.-Mexico border, and a municipality-specific drought index. More details on these data are provided in Appendix C.2.

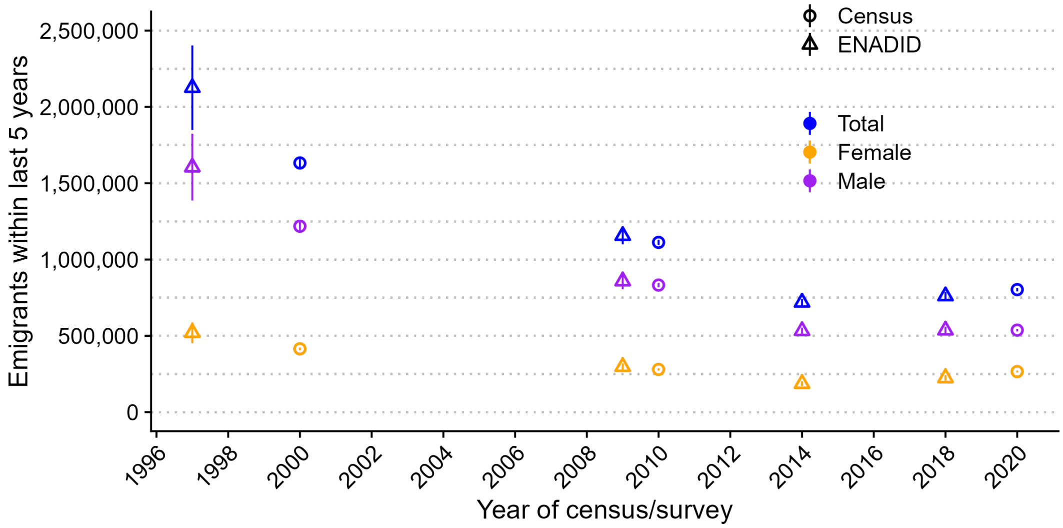
In all, I use data from the year 2000, which is when emigration flows from Mexico started decreasing drastically, until 2020. Having described the data, I proceed to answer 1) whether there is a change in the share of female emigrants, and 2) how does composition affect any changes in this share? For clarity, I explain the analytical approach in each question section.

## 3.4 Patterns of Mexican emigration

Historically, Mexican emigration has been male-dominated. In the 1940s and 1960s, the U.S. Bracero program hired Mexican workers and prompted large flows of male migrants (Durand, 2017; Vézina, 2022). Cultural factors and traditions around the division of labor in Mexico also contributed to this pattern. Figure 3.1 shows that at the beginning of the century, the flows continue to have large numbers of male migrants. However, since 1996, there has been a decline in all emigrants, with a noticeable decrease in male emigrants. For instance, the ENADID suggests that there were about 1.6 million male emigrants in 1997; by 2018 the ENADID estimated only half a million. In the same years, female emigrants went from half a million to a quarter of a million. This suggests that male emigrants decreased by more than half over the period, which is more than the decrease in female emigrants.

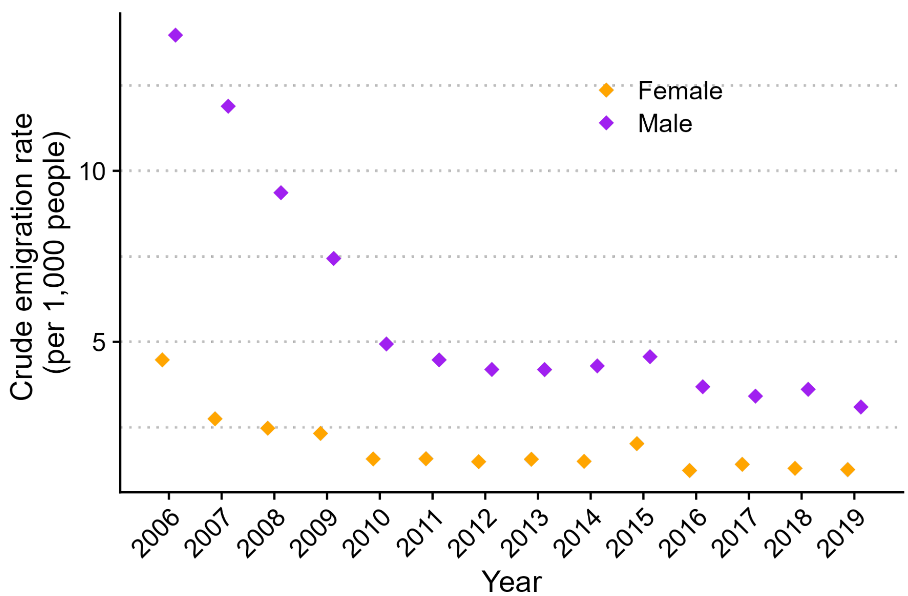
These counts do not take into account that age structure may differ between male and female emigrants. Figure 3.2 shows the female and male age-standardized emigration rates. To calculate these rates, the standard age distribution is the average of the female and male population distributions (by 10-year age groups), following Preston et al. (2001). By standardizing the rates, I remove the effect that different age distributions may have. Every year, male emigration rates are consistently higher than the female rates. However, male rates decreased sharply between 2006 and 2010. Female rates did not decline as sharply as male rates. After 2010, both rates move in similar patterns, with a slight downwards trend. Similar to figure 3.1, the decline is more pronounced for male emigrants.

**Figure 3.1:** Emigrants within the last five years from Mexico by sex from the Census and ENADID




Note: Point estimates include a 90% confidence interval calculated based on survey weights. Instrument year refers to the year when data was collected, which is not necessarily the year of emigration for the Census and ENADID.

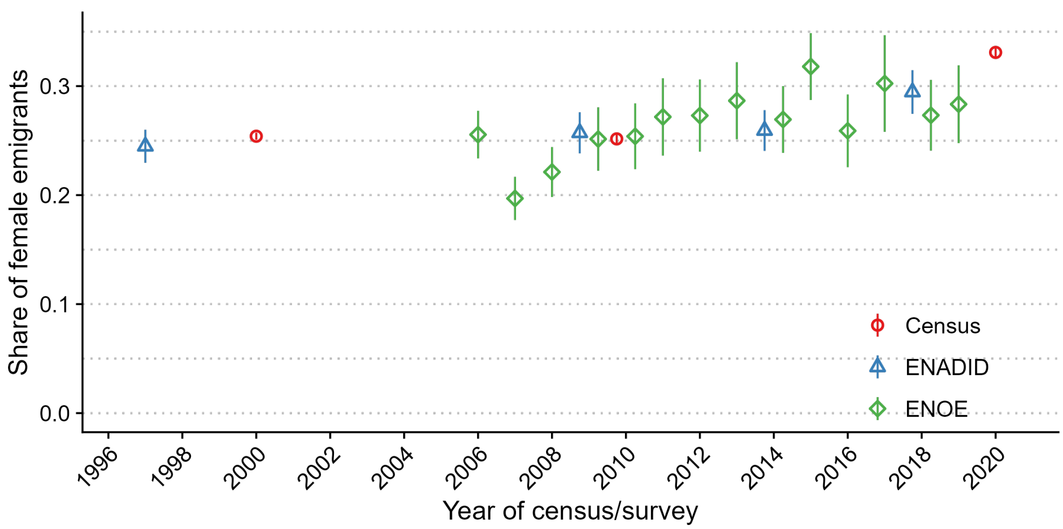
**Figure 3.2:** Age-standardized emigration rates.




Note: Own calculations from ENOE. The standard age distribution is the average of the female and male population distributions (by 10-year age groups).

Figure 3.3 shows the share of emigrant who are female. All data sources show that the share of female emigrants ranges between 0.2 and 0.35, which according to Donato and Gabaccia (2015) corresponds to a "male-predominant [e]migration". However, there is an increase in the share of female emigrants over time. Both the Census and the ENADID show that early in this century, only about 25% of migrants were female. In 2010, the share remained at the same level as 2000, but by 2020 it increased to 33%. That is, one out of three migrants were female rather than one in four just ten years earlier. In terms of Donato and Gabaccia (2015), Figure 3.3 suggests that Mexican emigration went from being "heavily male-predominant" to being "male-predominant", and that there is evidence for feminization as the share has increased over time.

**Figure 3.3:** Share of Mexican emigrants who are female has increased over time.




Note: Own calculations using the Census, ENADID and ENOE. Point estimates include a 90% confidence interval calculated based on survey weights. Instrument year refers to the year when data was collected, which is not necessarily the year of emigration for the Census and ENADID.

Overall, these results provide some evidence to suggest a slight feminization of emigration in Mexico *over time* with an important caveat: this does not reflect an increase in the number of female emigrants as has happened worldwide. In other words, the feminization happens because the number of male migrants has decreased while the female emigrants has remained more stable. What is so different between male and female emigrants that produces this trend? I propose a simple framework to analyze this question in the next section.

## 3.5 Contribution of changing composition and selection processes

The share of female emigrants is a measure of emigration; one that summarizes the decision to migrate between male and female potential migrants. This decision to migrate is a function of individual and household characteristics, and the context at the origin and destination, all of which may be interconnected. In addition, characteristics may change over time which adds another layer of complexity when we want to analyze why the share of female emigrants has increased over time. Here, instead of focusing on the contribution of single characteristics, I look at the contribution of characteristics altogether. This is in line with research that proposes that migrant characteristics should be analyzed in clusters rather than individually (Garip, 2017). Moreover, instead of focusing on changes in single quarters, I focus on yearly periods. Altogether, I analyze how changes in migrant characteristics and period context can explain the increase in the share female.

I adopt a decomposition approach based on the intuition from decompositions of aggregate measures that change one component while keeping other components constant (Blinder, 1973; Kitagawa, 1955; Oaxaca, 1973). To analyze changes in the share of female migrants, I sequentially fix the characteristics of migrants or the period. Differences between them are explained by the factor that is not fixed. When the determinants are fixed, then all changes are explained by the period. When the period is fixed, then all changes are explained by the determinants of emigration.

To estimate these contributions to the share female, I use a regression framework to estimate the probability of being an international migrant. In equation 3.1, $\beta^l$ measures the strength of the relationship between a characteristic and being an international emigrant, which I refer to as 'determinants of emigration', in period $l$. $\mathbf{X^k}$ shows the population composition in period $k$. Equation 3.1 is estimated for each $l$ period, such that $k = l$; the period of model estimation matches the period of the population composition. Then, these models are fitted on all the $k$ periods and multiplied by the household weight to obtain a predicted number of migrants, which I can use to calculate the predicted share of female emigrants. Equations 3.1 through 3.3 summarize the estimation process.

$$\text{Estimate model:} \quad Prob(Migrant_i^{k,l} = 1) = f(\mathbf{X^k}\beta^{\mathbf{l}}) \tag{3.1}$$

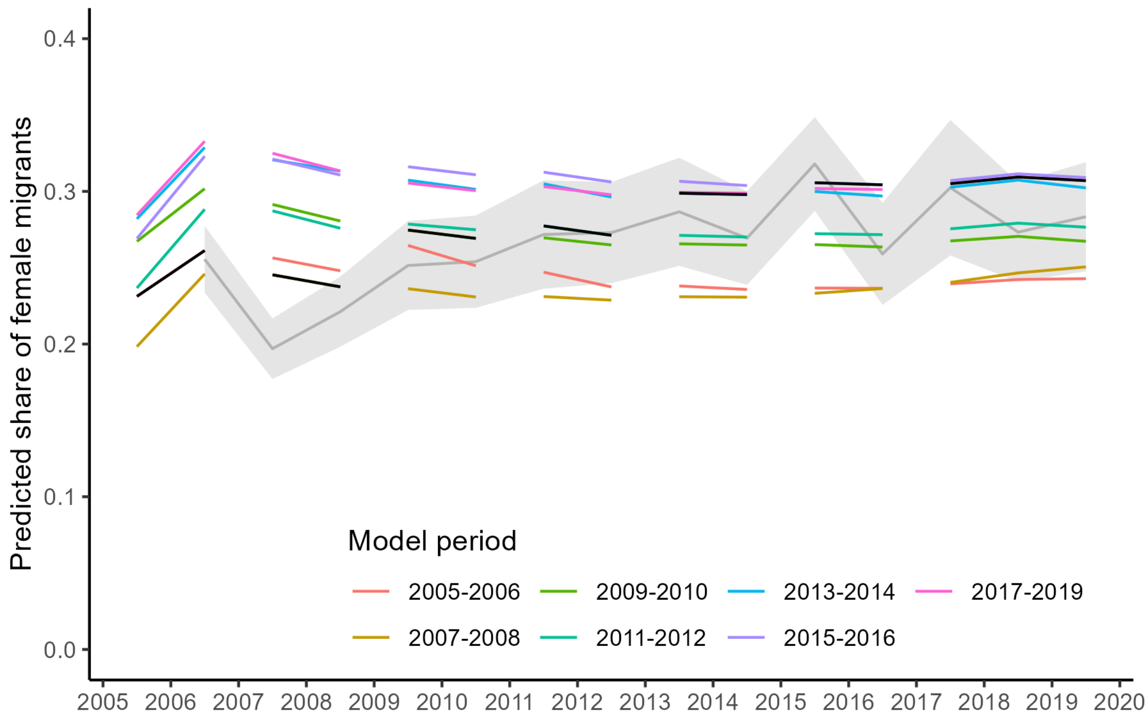
$$\text{Fit model for each } k \text{ period:} \quad Prob(\widehat{Migrant}_i^{k,l} = 1) = f(\mathbf{X^k}\widehat{\beta}^{\mathbf{l}}) \tag{3.2}$$

$$\text{Calculate weighted share of female emigrants} \tag{3.3}$$

For this analysis, I estimate logistic regressions where the dependent variable is a dichotomous variable for being an international emigrant. The independent variables are demographic, household, spatial and macroeconomic characteristics of individuals, which I obtained from the ENOE and a range of sources. For space, I explain the reasoning behind these variables in section C.1 and the full variable definitions in section C.2 of the appendix. I choose to estimate logistic regressions since the predicted probabilities are bound to lie within [0,1]. Appendix C.3 shows the odds ratios from the estimated logistic regressions. In the following graphs, I include the observed share of migrants who are female (with a confidence interval estimated from survey uncertainty). I divide the 2005-2019 period in two-year periods where I estimate the logistic regression.

Figure 3.4 shows the predicted share of female migrants of specific models in specific periods. To highlight comparisons within-period, the predictions are not continuous lines. Comparing shares within columns is analogous to fixing the period, and all differences are explained by composition. Comparing shares of the same model between columns indicates the contribution of the context.

**Figure 3.4:** Predicted share of migrants who are female.




Note: Observed share of female migrants in grey with a 95% confidence interval. Black lines correspond to prediction periods that match model estimation periods.

Within columns, the highest predicted share comes from the estimations using the 2013-2019 data. If the determinants of emigration of 2013-2019 were applied to all periods, we would see a high share of female emigrants. For instance, in 2005-2006 the predicted share (with determinants from 2013-2019) would have been about 9 percentage points higher. This difference, between the yellow and purple lines, persists during the 2005-2019 period, which shows how different determinants are in more recent years.

Between each column, the order of the predicted shares does not change substantially. However, the predictions are clustered by years: the highest shares come from the 2013-2014, 2015-2016 and 2017-2019 models. Next, follows the 2011-2012 and the 2009-2010 models. At the bottom the 2005-2006 and 2007-2008 models. This stability suggests that the composition of the population is relatively steady as well. That is, there is no striking effect of population composition on the increasing share of female emigration. In essence, figure 3.4 suggests that part of the feminization of emigration in Mexico is explained by changes in determinants of emigration and but less by the period composition.

Finally, the predicted shares can be compared to the observed shares. The black lines come from models estimated in the periods. With the exception of the 2007-2008 fitted share, the black lines lie within the observed confidence interval, but are larger than the point estimates. The demographic, economic and contextual factors of the regression are enough to explain the observed trends, but slightly overestimate the share of female migrants, especially for the periods of 2009-2010, 2013-2014 and 2017-2019. It is likely that unobserved factors are driving this wedge, which requires future analysis. Despite this limitation, the share increases over time, which means that even when important determinants of emigration are taken into account, there is evidence for the process of feminization.

### 3.5.1 Sex-blind processes

Results from the previous figures highlight that changes in the determinants of emigration may help explain the evidence for feminization. However, being a share, it's unclear if the determinants are directly explained by female or male selection into emigration.[3] One way to understand this better is to estimate two models per period, one for each sex. Then, assume that the other sex is subject to the same determinants of emigration, and predict the probability of being an international emigrant. For instance, male models are estimated on male data, then used to predict on male and female data. Using the observed sex categories, I calculate the share female as explained above. By doing this, I am effectively asking: what would the share female be if the female migrants experienced selection just like male migrants, and vice versa? However, for my purposes this extreme analysis is useful to pinpoint the contribution of being male or female.

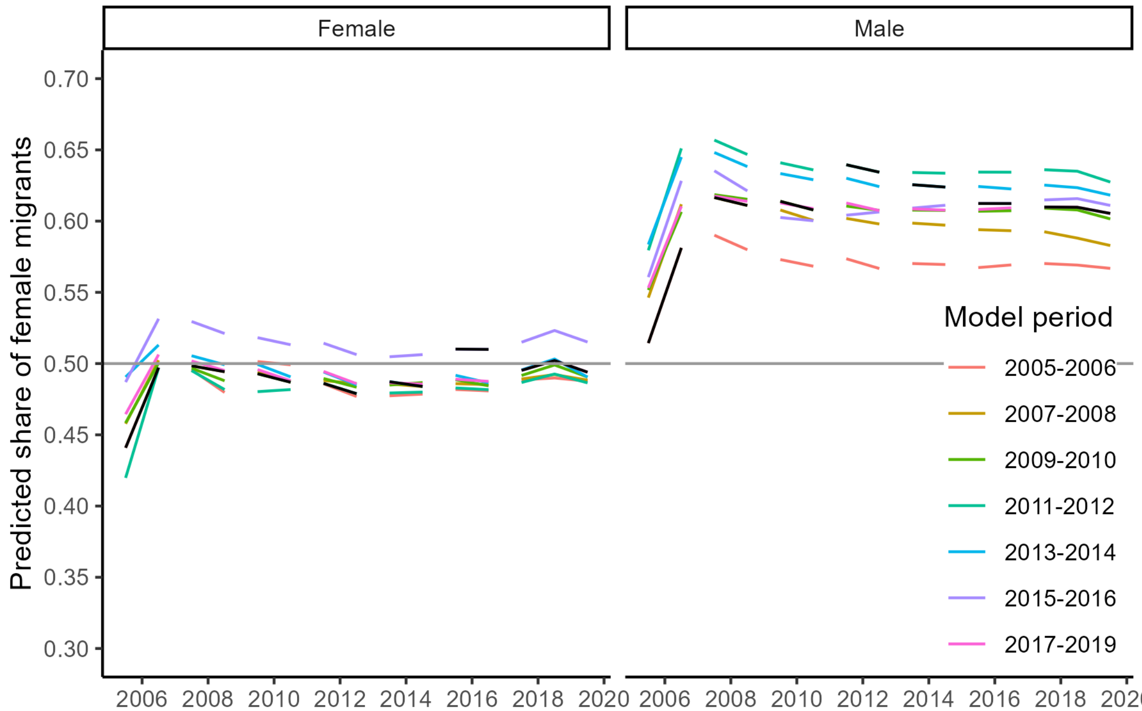
The range of predicted shares in figure 3.5 is substantially larger than the observed in both extremes of the analysis. If women were treated like men, then the share female would be larger than 50%, and suggesting a very strong process of feminization. If men were treated like women, the share would still be below 0.5, our marker of equality, but with an upward trend over time. One way to interpret these graphs is that for each panel, the model coefficients are either female or male and they are weights that are applied to female or male populations (migrants and non migrants). In the right panel, the female population has such a composition that when weighted by the determinants of male emigration, leads to a large share of female migrants. However, in the left panel, the share female is close to 50% because the male population and the female population are weighted similarly by the determinants of female emigration. In either case, the unique combination of determinants and population composition would lead to a sex-balanced emigration or a female-dominant emigration. In reality, the share is substantially smaller, and likely reflects the effect of unobserved factors on sex-specific emigration.

## 3.6 Discussion and conclusions

There have been mixed conclusions from work on feminization, (Anastasiadou et al., 2023; Christou & Kofman, 2022) but most point to a limited process of feminization (or at least not to the extent where more than half of flows are female). However, there is some evidence that some subgroups of migrants have a higher share female (i.e., the highly educated). Using detailed individual-level data on migrants from Mexico, I i) document trends of Mexican emigration by sex to analyze if there is a feminization of emigration, and ii) consider the effect of changing population composition and selection processes. In the case of Mexican

[3] I include the predicted counts of migrants in Appendix C.4. Figures C.1 through C.3 in the appendix show that the predicted counts varies substantially across models.

**Figure 3.5:** Predicted share of migrants who are female by models estimated in different periods.




Note: Black lines correspond to prediction periods that match model estimation periods.

emigration, plenty of research has documented trends in who migrated but often either for men or in an earlier period (Garip, 2017; Massey & Espinosa, 1997; Villarreal, 2014; Zenteno et al., 2013). This chapter fills a gap in the literature by considering the female population exposed to emigration using more recent data and in the context of declining out-migration from Mexico. Indeed, the ENOE's panel structure allows female emigrants to be more visible, despite the fact that emigration is a rare event. The results suggest that there is an increase in the share of female emigration during the current century but that it is not driven by increasing numbers of female emigrants.

An analysis of the feminization of emigration cannot be done without acknowledging how the pathways to entry to emigration are different between men and women. Moreover, selection patterns can change over time and reflect the changing composition of the population. As such, this chapter distinguishes between the changes in selection into emigration and in composition on the share of female, a summary measure of feminization in emigration. Overall, I find evidence that the increasing share of migrants who are female arises mostly from changes in determinants of emigration. During 2008 and 2011, population composition helped explain the share, but selection processes seem to overpower the compositional effect.

The decomposition approach is flexible in answering a range of questions as long as the researcher has detailed data. For instance, what if men were women? what if women were men? This particular exercise was helpful to identify that if all women were treated like men, then there would be a larger number and share of female migrants. This large gap is evidence of the effect of sex, on migrant selection.

While I chose the share of female migrants other metrics can be used to document the differences by selection and composition, for example: total predicted female and male count or the sex ratio. An extension of this work would look at the specific variables that explain the share of female migrants.

There are certain limitations to consider. First, the data does not capture information on the gender of migrants. By using biological sex, I am limited in the connections of female or male lived experiences that can directly influence the ability to migrate. However, to the extent that respondents understand sex and gender to be similar, they may report on gender rather than sex. Furthermore and despite the detailed data, more can be included. With the 2023 ENADID available, I could extend this analysis to see whether feminization has changed after the pandemic. Furthermore, we cannot fully understand feminization without exploring the composition of Mexican immigrants at their destinations (Donato et al., 2011). More research is needed to include representative household surveys from the main destination of Mexican migrants, i.e., the U.S, Canada and Spain.

The discussion and measurement of feminization bring out certain questions about what specific change should be of interest for researchers and policymakers. As Bircan and Yilmaz (2022) underline, should the goal be to have a higher share or *number* of migrants who are female? As previously mentioned, the former can happen when the number of male migrants decreases and female migrants remains constant. In addition to the absolute and relative questions, there's also the consideration that not all emigration is voluntary (Schewel, 2020). Therefore, the absence of migrants may be desirable if what people want is to remain in their country, and in this case the correct indicator should be the share of voluntary migrants who are female. An extension of this project would involve identifying measures of voluntary and involuntary emigration, and identifying the composition of each group in terms of gender and other characteristics.

The World Migration Report 2024 by the International Migration Organization (IOM) pushes to move the focus from female-male emigration to gender and the gendered process of emigration. They underline that "a gender-responsive approach is not only about women's rights but more broadly about striving for gender equality, although today's reality remains that of disproportionate gender discrimination against women and persons with diverse gender identities, including throughout the emigration cycle" (Bauloz et al., 2024, p.31). A first step to a "gender-sensitive approach" is to obtain good quality data and document trends, much like this work does. This descriptive work can shed light on ways that Mexican emigration has changed in the last 20 years, while bringing our attention to female migrants.

# Chapter 4

# Conclusion

Migration is a constantly evolving demographic process. With a unique history of migration and geographic position, Mexico will continue to experience different forms of migration. According to the most recent Demographic Conciliation (2023) from Mexico's National Population Council, CONAPO, the net migration rate should continue to be negative and oscillate around one per thousand until 2050. As such, analyzing past migration trends helps set up those for the future. This dissertation contributes to our knowledge of trends of Mexican migration at the beginning of the $21^{st}$ century.

Migration research that wishes to be representative suffers from limited data availability. The validation of the ENOE opens the door to questions that push the frontier in migration research. Past literature had expressed concerns about the representativity of the ENOE because it is not a survey designed for demographic measures (Pederzini, 2018). However, this chapter provides solid evidence that the ENOE is a rich and representative source of migration data. In a quantitative field such as Demography, our research will only improve if we have data available. The ENOE can answer new and exciting questions about migration, not only regarding emigration but also immigrants to Mexico. Relative to emigration, the ENOE was used substantially less to study immigration. Given the increasing flow of immigrants going through Mexico to arrive in the U.S., it would be essential to gather evidence of the composition of those who stay in Mexico. For instance, what are their educational and employment profiles? The ENOE can also be used for causal questions regarding the short-term effects of immigration.

There is increasingly an effort to re-purpose existing data to understand demographic patterns (Kashyap, 2021), but newer data should be used with caution and awareness of its limitations. In the case of the ENOE, researchers should not estimate the total counts of migrants but rather relative measures (shares or ratios). As seen throughout this dissertation, the ENOE may also be used for regression analysis. The first chapter is an important contribution to existing migration data in Mexico.

The ENOE is rich in variables, but one particular variable allowed Rui Carvalho and I to understand the stage prior to migration. Preparing to migrate consists of concrete actions to become migrants. Much of the literature on pre-migration decisions focused on a less concrete step: aspiring to migrate. This often suggested high levels of aspiration to migrate. In the second chapter, we find that preparing to migrate is less prevalent and that not all preparations lead to migration. Moreover, not all international migrants prepare beforehand. This last result contradicts migration theory, which assumes that migrants are rational actors who seek to minimize the cost of migration. Preparing should be a form of cost reduction. However, our results suggest that part of the ability to prepare comes from specific characteristics. This selection into preparations is a form of inequality within aspiring migrants, which had not been documented before. Our findings on preparations contribute to expand the migration decision process. We find that preparations are associated with almost immediate changes in employment outcomes for those who migrate and those who remain in Mexico. Therefore, understanding preparations to migrate broadens the impact of migration: i.e., not on moving across the border, but the pre-emptive actions that lead up to it.

Another form of inequality that I analyze is based on the sex composition of international migrants from Mexico. In the third chapter, I consider the extent to which the share of female migrants has changed in Mexico. Although migration from Mexico continues to be male-dominated, the share of female migrants increased from 25% to 33% between 2000 and 2020. The increase is enough to consider that there is a feminization process (Donato & Gabaccia, 2015). Worldwide, the share of female migrants is substantially more prominent, which is in contrast to Mexico. The low share of female migrants results from gendered barriers to migration, which is the takeaway from the decomposition analysis. How does this analysis contribute to understanding future migration? Female migration has remained more stable in size and determinants, unlike male migration. The stability in flows can have implications for migrants' households and communities because of remittances. Traditionally, men have been the primary source of remittances. As the share of female migrants increases, this may make women a more important source of economic support for recipients in Mexico, a trend which could have broader implications for gender roles in Mexican society.

This dissertation answers substantive and technical questions to better inform our view on Mexican migration. However, it also raises important issues regarding existing quantitative data. Relative to other developing nations, Mexico has high-quality data on migration from its decennial Census and demographic household surveys. The first chapter now allows us to add the ENOE to this list. However, no single data are nationally representative, contain rich covariates, collect information about the destinations of migrants, and include pre and post-migration measures. As I've developed in this dissertation, migration may occur at a single point in life, but may affect choices before it materializes. Between aspirations, preparations, and actual migration, how long does the process take? Relative to the life course, when do these stages occur? Answering these questions will require data that follows individuals during their lifetime and tracks their migration process. Here, a mixed-methods approach may be preferred.

Even when Mexico has advanced data for migration, one component that needs to be added is the connection to data at the destination. This is important because the context at the destination is a pull factor for migration. No data are perfect, neither at the origin nor the destination. Still, if migration from an origin could be matched to outcomes at the destination, researchers could directly measure the impact of migration on migrants. Although this is ideal for research, it invades the privacy of migrants, particularly those in vulnerable situations or who are undocumented. Instead, there should be more efforts between researchers to probabilistically match individual migration records across different data. With this unified data and more measures of undocumented migration, we can obtain a more comprehensive understanding of migration patterns over time.

This dissertation focuses on the case of Mexican migration, but the results may be informative of other migration streams. For instance, these streams could have similar characteristics to the Mexico-U.S. relationship: sustained flows between bordering (or close) countries, destinations with a demand for cheaper labor and origins with an excess pool of labor, and harsh immigration policies at the destination. An example of this stream could be the flow from Eritrea to Saudi Arabia. Even when migration streams do not have all these characteristics, the Mexican case can still be informative. Mexico is an example of how demographic growth requires of an 'escape valve', and how migration is the answer (Vézina, 2022). Although the decision to migrate may have individual reasons, it operates within a larger structure, such that all aggregate and individual factors jointly affect the decision to migrate. We learn and generalize from Mexican migration that there is no single determinant of migration, rather a combination of many. However, not all streams share the characteristics of the Mexico-U.S. stream, which is why migration research on different dyads is also necessary to inform migration theory. Moving forward, more research on specific origins and destinations is necessary.

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# Appendix A

# Appendix for Chapter 1

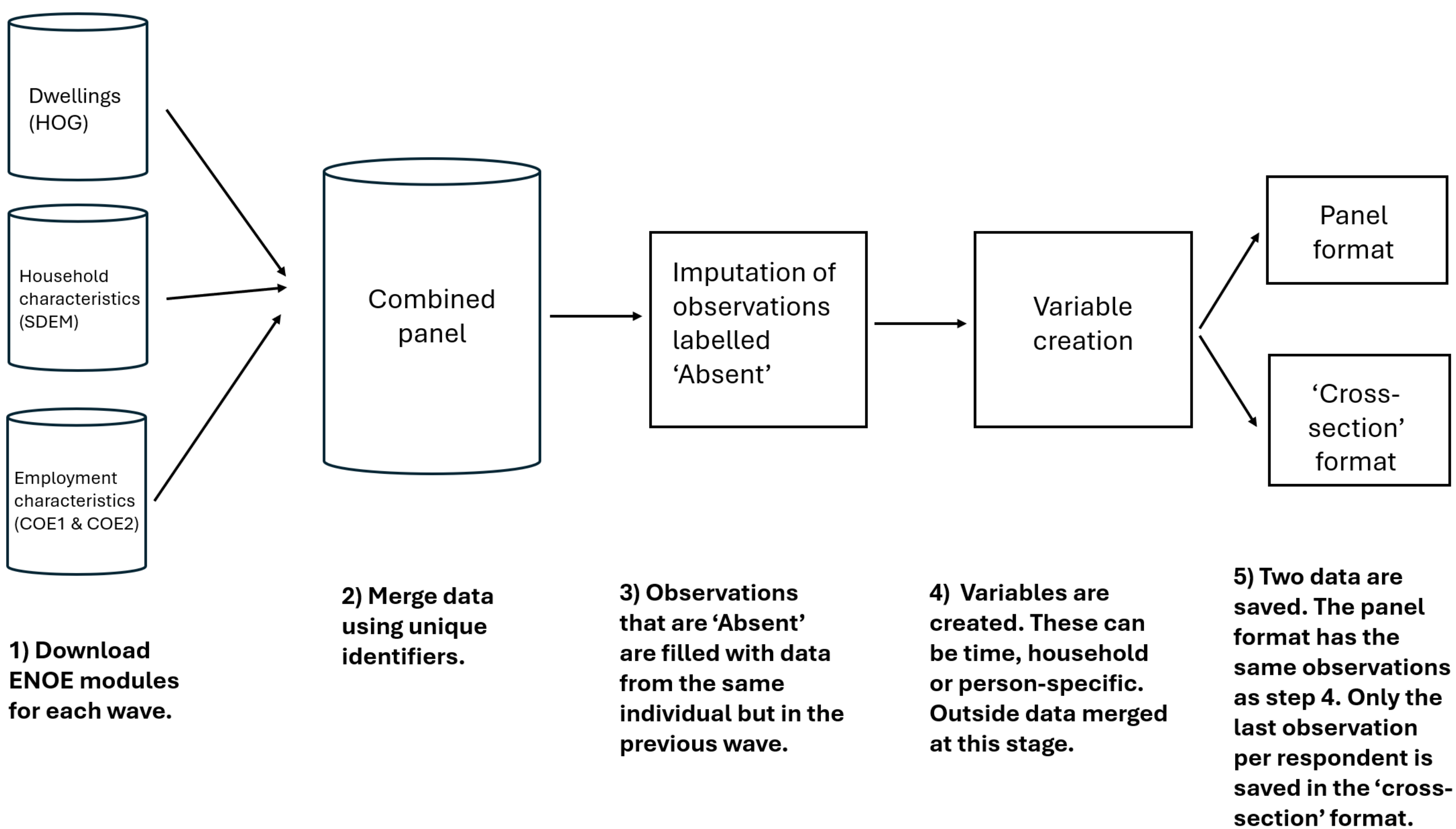
## A.1 Timeline of ENOE, ENADID and Census

**Table A.1:** Comparable periods of analysis

| Year | ENADID period | Census period | ENOE period |
|---|---|---|---|
| 2010 | | May 31st - June 25th | 2010 Q2 |
| 2009 | May 18th - July 10th | | 2009 Q2 |
| 2014 | August 4th - September | | 2014 Q3 |
| 2018 | August 13th - October 5th | | 2018 Q3 |
| 2020 | | March 2nd - 27th | 2020 Q1 |

## A.2 ENOE pre-processing

**Figure A.1:** Workflow to process and merge all ENOE waves.



## A.3 Questions in Census, ENADID and ENOE

**Table A.2:** Available questions in ENADID and Census on migration, and inference from the ENOE on migrants.

| Question | ENADID | | | Census | | ENOE |
|---|---|---|---|---|---|---|
| | 2009 | 2014 | 2018 | 2010 | 2020 | |
| In what state of Mexico or country were you born? | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| A year ago, in [date], en which state of Mexico or country did you live? | ✓ | ✓ | ✓ | | | Inferred |
| Why did [the respondent] stop living in the state or country a year ago? | | ✓ | ✓ | | | Inferred |
| Five years ago, in [date], en which state of Mexico or country did you live? | ✓ | ✓ | ✓ | ✓ | ✓ | |
| During the last 5 years, that is from [time 1] to [time 2], has any person who lived here (with you or in this dwelling) gone to... | ...live to the USA? | ...live or work to another country? | | ... live in another country? | ... live in another country? | |
| How many people? | ✓ | ✓ | ✓ | ✓ | ✓ | |
| When [migrant] last left, did they live with you? | ✓ | ✓ | ✓ | ✓ | ✓ | |
| What is the sex of [migrant] | ✓ | ✓ | ✓ | ✓ | ✓ | Sex of respondent |
| How many years did [the migrant] have when they last left? | ✓ | ✓ | ✓ | ✓ | ✓ | Age of respondent |
| In what month and year did [the migrant] leave to another country? | ✓ | ✓ | ✓ | ✓ | ✓ | Quarter when declared absent |
| What was the main reason that [the migrant] left for the most recent trip? | | ✓ | ✓ | | ✓ | What was the main reason for the absence? |

**Table A.2:** Available questions in ENADID and Census on migration, and inference from the ENOE on migrants.

| Question | ENADID | | | Census | | ENOE |
|---|---|---|---|---|---|---|
| | 2009 | 2014 | 2018 | 2010 | 2020 | |
| In which state of Mexico did [the migrant] live prior to the most recent trip? | | ✓ | ✓ | ✓ | ✓ | State of residence of household |
| What was the country of destination? | | ✓ | ✓ | ✓ | ✓ | |
| What state of the USA did [the migrant] go to? | ✓ | ✓ | ✓ | | | |
| What document document did [the migrant] use? | ✓ | ✓ | ✓ | | | |
| In which state of the USA does [the migrant] currently live? | | ✓ | ✓ | | | |
| When [the migrant] returned to Mexico, in which state of the USA or country did they live in before? | | ✓ | ✓ | | | |
| What is the current country of residence of [the migrant]? | ✓ | ✓ | ✓ | ✓ | ✓ | |
| In which month and year did they return to Mexico? | ✓ | ✓ | ✓ | ✓ | ✓ | |
| What was the main reason that [the migrant] returned to Mexico for? | | ✓ | ✓ | | | |
| Does [the returned migrant] currently live in this dwelling? | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Does anyone in this dwelling receive money from someone living in another country? Or from another household within Mexico? | Does [respondent] receive any money from family members in another country? Or within the country? | | Last month did [respondent] receive any support from someone in another country or another state in Mexico? | | | ✓ |

## A.4 Descriptive tables

**Table A.3:** Descriptive statistics of **international emigrants** from select variables over time and between ENOE, ENADID and Census

| | 2009 | | 2010 | | 2014 | | 2018 | | 2020 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ENOE | ENADID | ENOE | Census | ENOE | ENADID | ENOE | ENADID | ENOE | Census |
| **International emigrants within 1 year** | | | | | | | | | | |
| Count | 2048 | 985 | 1617 | 34116 | 1189 | 804 | 1171 | 1123 | 1045 | 44292 |
| **Share female** | | | | | | | | | | |
| | 0.24 | 0.17 | 0.23 | 0.23 | 0.28 | 0.25 | 0.27 | 0.29 | 0.28 | 0.29 |
| | (0.01) | (0.02) | (0.02) | (0.01) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.01) |
| **Mean age** | | | | | | | | | | |
| | 29.92 | 29.9 | 30.58 | 32.02 | 31.1 | 34.36 | 31.17 | 33.44 | 31.45 | 31.08 |
| | (0.47) | (0.7) | (0.64) | (0.19) | (0.73) | (0.73) | (0.74) | (0.81) | (0.92) | (0.16) |
| **Size of locality** | | | | | | | | | | |
| <2,500 | 0.37 | 0.46 | 0.36 | 0.45 | 0.39 | 0.41 | 0.39 | 0.44 | 0.42 | 0.35 |
| | (0.02) | (0.02) | (0.02) | (0.01) | (0.02) | (0.02) | (0.01) | (0.02) | (0.02) | (0.01) |
| 2,500-14,999 | 0.16 | 0.21 | 0.18 | 0.16 | 0.16 | 0.15 | 0.14 | 0.15 | 0.13 | 0.17 |
| | (0.01) | (0.03) | (0.02) | (0) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) | (0) |
| 15,000-99,999 | 0.13 | 0.11 | 0.13 | 0.14 | 0.14 | 0.13 | 0.12 | 0.1 | 0.09 | 0.14 |
| | (0.01) | (0.01) | (0.01) | (0) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0) |
| 100,000> | 0.34 | 0.22 | 0.33 | 0.26 | 0.31 | 0.32 | 0.35 | 0.31 | 0.36 | 0.34 |
| | (0.01) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | (0.01) |
| **International emigrants within 5 years** | | | | | | | | | | |
| Count | 13622 | 4872 | 11460 | 156440 | 5487 | 2289 | 5001 | 2611 | 4834 | 120099 |
| **Share female** | | | | | | | | | | |
| | 0.18 | 0.18 | 0.23 | 0.25 | 0.27 | 0.26 | 0.29 | 0.29 | 0.29 | 0.33 |
| | (0.01) | (0.01) | (0.01) | (0) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0) |
| **Mean age** | | | | | | | | | | |
| | 28.6 | 26.04 | 28.85 | 27.77 | 30.74 | 31.71 | 30.47 | 31.54 | 30.68 | 29.02 |
| | (0.21) | (0.28) | (0.21) | (0.08) | (0.38) | (0.38) | (0.34) | (0.46) | (0.37) | (0.09) |

**Table A.3:** Descriptive statistics of **international emigrants** from select variables over time and between ENOE, ENADID and Census

| | 2009 | | 2010 | | 2014 | | 2018 | | 2020 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ENOE | ENADID | ENOE | Census | ENOE | ENADID | ENOE | ENADID | ENOE | Census |
| **Size of locality** | | | | | | | | | | |
| <2,500 | 0.4 | 0.44 | 0.39 | 0.39 | 0.36 | 0.33 | 0.38 | 0.37 | 0.39 | 0.3 |
| | (0.01) | (0.01) | (0.01) | (0) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0) |
| 2,500-14,999 | 0.15 | 0.19 | 0.16 | 0.16 | 0.15 | 0.14 | 0.15 | 0.14 | 0.15 | 0.16 |
| | (0.01) | (0.01) | (0.01) | (0) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0) |
| 15,000-99,999 | 0.14 | 0.12 | 0.14 | 0.14 | 0.15 | 0.13 | 0.12 | 0.11 | 0.11 | 0.14 |
| | (0.01) | (0.01) | (0.01) | (0) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0) |
| 100,000> | 0.3 | 0.25 | 0.31 | 0.31 | 0.34 | 0.4 | 0.35 | 0.38 | 0.35 | 0.41 |
| | (0.01) | (0.01) | (0.01) | (0) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0) |

Note: Own elaboration using *svydesign* R package. Standard errors in parentheses.

**Table A.5:** Descriptive statistics of **lifetime immigrants** from select variables over time and between ENOE, ENADID and Census.

| | 2009 | | 2010 | | 2014 | | 2018 | | 2020 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ENOE | ENADID | ENOE | Census | ENOE | ENADID | ENOE | ENADID | ENOE | Census |
| **Share by origin** | | | | | | | | | | |
| Same state | 0.8198 | 0.8365 | 0.8183 | 0.806 | 0.8227 | 0.8152 | 0.8271 | 0.8197 | 0.8273 | 0.817 |
| | (0.0018) | (0.0023) | (0.0018) | (0.0011) | (0.0018) | (0.0018) | (0.0019) | (0.0016) | (0.0019) | (0.0011) |
| Other state | 0.1722 | 0.156 | 0.1732 | 0.1827 | 0.1696 | 0.1765 | 0.1653 | 0.1716 | 0.1637 | 0.1722 |
| | (0.0018) | (0.0023) | (0.0018) | (0.0011) | (0.0018) | (0.0017) | (0.0018) | (0.0015) | (0.0018) | (0.0011) |
| USA | 0.0059 | 0.005 | 0.0065 | 0.0066 | 0.0058 | 0.0059 | 0.0055 | 0.0064 | 0.0059 | 0.006 |
| | (0.0003) | (0.0002) | (0.0003) | (0.0001) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0003) | (0.0001) |
| Other country | 0.002 | 0.0022 | 0.002 | 0.002 | 0.0018 | 0.0023 | 0.002 | 0.0022 | 0.0029 | 0.0033 |
| | (0.0002) | (0.0002) | (0.0003) | (0.0001) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0003) | (0.0001) |
| Not specified | 0.000 | 0.0004 | 0.000 | 0.0027 | 0.000 | 0.0001 | 0.000 | 0.000 | 0.0002 | 0.0015 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0001) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0001) |
| **Share female** | | | | | | | | | | |
| Same state | 0.51 | 0.51 | 0.51 | 0.51 | 0.51 | 0.51 | 0.52 | 0.51 | 0.52 | 0.51 |
| | (0.001) | (0.001) | (0.001) | (0) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0) |
| Other state | 0.53 | 0.53 | 0.53 | 0.52 | 0.53 | 0.52 | 0.53 | 0.52 | 0.52 | 0.52 |
| | (0.003) | (0.003) | (0.003) | (0.001) | (0.003) | (0.002) | (0.003) | (0.002) | (0.003) | (0.001) |
| USA | 0.5 | 0.48 | 0.5 | 0.49 | 0.48 | 0.46 | 0.5 | 0.5 | 0.5 | 0.5 |
| | (0.016) | (0.016) | (0.015) | (0.004) | (0.013) | (0.012) | (0.015) | (0.012) | (0.013) | (0.004) |
| Other country | 0.51 | 0.49 | 0.48 | 0.5 | 0.52 | 0.5 | 0.47 | 0.48 | 0.5 | 0.48 |
| | (0.026) | (0.028) | (0.024) | (0.007) | (0.03) | (0.023) | (0.024) | (0.021) | (0.022) | (0.005) |
| Not specified | 0.58 | 0.55 | 0.43 | 0.51 | 0.89 | 0.41 | 0.42 | 0.84 | 0.68 | 0.52 |
| | (0.145) | (0.054) | (0.121) | (0.006) | (0.097) | (0.089) | (0.168) | (0.096) | (0.039) | (0.008) |
| **Mean age** | | | | | | | | | | |
| Same state | 27.8 | 27.99 | 27.93 | 27.4 | 29.05 | 28.94 | 30.51 | 30.49 | 31.03 | 30.16 |
| | (0.08) | (0.09) | (0.08) | (0.03) | (0.08) | (0.08) | (0.08) | (0.07) | (0.08) | (0.03) |
| Other state | 38.55 | 39.02 | 38.45 | 37.46 | 39.95 | 40.01 | 41.15 | 41.38 | 42.01 | 40.83 |
| | (0.18) | (0.2) | (0.19) | (0.07) | (0.2) | (0.17) | (0.21) | (0.17) | (0.2) | (0.07) |

**Table A.5:** Descriptive statistics of **lifetime immigrants** from select variables over time and between ENOE, ENADID and Census.

| | 2009 | | 2010 | | 2014 | | 2018 | | 2020 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ENOE | ENADID | ENOE | Census | ENOE | ENADID | ENOE | ENADID | ENOE | Census |
| USA | 14.44 | 14.58 | 12.38 | 13.78 | 14.16 | 13.12 | 17.13 | 16.67 | 16.42 | 18.2 |
| | (0.61) | (0.59) | (0.46) | (0.33) | (0.44) | (0.32) | (0.67) | (0.56) | (0.83) | (0.23) |
| Other country | 37.05 | 41.05 | 38.66 | 39.24 | 39.94 | 37.73 | 40.65 | 37.9 | 38.35 | 38.16 |
| | (1.25) | (1.39) | (1.85) | (0.43) | (1.51) | (1.02) | (1.58) | (1.05) | (1.48) | (0.29) |
| Not specified | 26.7 | 28.54 | 25.84 | 29.29 | 60.5 | 37 | 45.41 | 44.95 | 50.44 | 29.01 |
| | (4.15) | (2.14) | (7.07) | (0.35) | (2.78) | (4.14) | (5.11) | (7.71) | (5.03) | (0.5) |

Note: Own elaboration using *svydesign* R package. Standard errors in parentheses.

**Table A.7:** Descriptive statistics of **immigrants by place of residence 1 year** earlier from select variables over time and between ENOE and ENADID.

| | 2009 | | 2014 | | 2018 | |
|---|---|---|---|---|---|---|
| | ENOE | ENADID | ENOE | ENADID | ENOE | ENADID |
| **Share by origin** | | | | | | |
| Same state | 0.9931 | 0.9878 | 0.9916 | 0.9884 | 0.9906 | 0.9868 |
| | (0.0011) | (0.0005) | (0.001) | (0.0004) | (0.001) | (0.0004) |
| Other state | 0.001 | 0.0085 | 0.0012 | 0.0098 | 0.0012 | 0.0115 |
| | (0.0002) | (0.0005) | (0.0003) | (0.0004) | (0.0002) | (0.0004) |
| Other country | 0.0008 | 0.0036 | 0.0003 | 0.0017 | 0.0008 | 0.0017 |
| | (0.0002) | (0.0002) | (0.0001) | (0.0001) | (0.0003) | (0.0001) |
| Not specified | 0.0051 | 0.0001 | 0.007 | 0.0001 | 0.0074 | 0 |
| | (0.001) | (0) | (0.001) | (0) | (0.0009) | (0) |
| **Share female** | | | | | | |
| Same state | 0.51 | 0.51 | 0.52 | 0.51 | 0.52 | 0.51 |
| | (0.0023) | (0.001) | (0.0022) | (0.0008) | (0.0022) | (0.0009) |
| Other state | 0.6 | 0.48 | 0.56 | 0.47 | 0.43 | 0.46 |
| | (0.0712) | (0.0116) | (0.0643) | (0.01) | (0.0753) | (0.0095) |
| Other country | 0.25 | 0.28 | 0.29 | 0.32 | 0.43 | 0.32 |
| | (0.1005) | (0.0171) | (0.1021) | (0.0244) | (0.0696) | (0.021) |
| Not specified | 0.49 | 0.49 | 0.5 | 0.86 | 0.52 | 0.37 |
| | (0.0532) | (0.1079) | (0.0309) | (0.0889) | (0.0343) | (0.3295) |
| **Mean age** | | | | | | |
| Same state | 30.46 | 30.23 | 32.02 | 31.34 | 33.34 | 32.78 |
| | (0.1957) | (0.0794) | (0.1857) | (0.0692) | (0.1784) | (0.0663) |
| Other state | 24.41 | 24.6 | 25.72 | 27.56 | 30.62 | 26.84 |
| | (2.8787) | (0.533) | (3.5513) | (0.4132) | (2.8109) | (0.3844) |
| Other country | 29.29 | 28.77 | 36.08 | 30.4 | 29.11 | 35.53 |
| | (4.3536) | (0.7271) | (5.1776) | (1.0215) | (3.0969) | (0.9088) |
| Not specified | 25.79 | 4.22 | 27.17 | 53.03 | 20.81 | 3.11 |
| | (1.4556) | (1.5386) | (1.5991) | (3.7646) | (1.09) | (0.9885) |

Note: Own elaboration using *svydesign* R package. Standard errors in parentheses.

## A.5 Alternative RMSE

**Table A.9:** Root Mean Square Error by interval of international emigration for all yearly observations within migrant categories and variables.

| Variable | Interval | ENOE vs ENADID | ENOE vs Census | ENADID vs Census |
|---|---|---|---|---|
| Share female | 1 year | 0.0410 | 0.0110 | 0.0392 |
| | 5 years | 0.0091 | 0.0338 | 0.0559 |
| Mean age | 1 year | 2.2892 | 1.0511 | 2.2407 |
| | 5 years | 1.6963 | 1.4008 | 2.1631 |
| **Share by size of locality** | | | | |
| All | 1 year | 0.0496 | 0.0544 | 0.0437 |
| | 5 years | 0.0325 | 0.0382 | 0.0423 |
| <2,500 | 1 year | 0.0598 | 0.0808 | 0.0626 |
| | 5 years | 0.0255 | 0.0635 | 0.0623 |
| 2,500-14,999 | 1 year | 0.0287 | 0.0319 | 0.0392 |
| | 5 years | 0.0227 | 0.0077 | 0.0215 |
| 15,000-99,999 | 1 year | 0.0150 | 0.0339 | 0.0334 |
| | 5 years | 0.0181 | 0.0189 | 0.0220 |
| 100,000> | 1 year | 0.0723 | 0.0560 | 0.0325 |
| | 5 years | 0.0522 | 0.0371 | 0.0482 |

**Table A.10:** Root Mean Square Error after removing all 'Not specified' categories for all yearly observations within migrant categories and variables.

| variable | ENOE vs ENADID | ENOE vs Census | ENADID vs Census |
|---|---|---|---|
| **Immigrants by place of birth** | | | |
| Share by origin | 0.0079 | 0.0072 | 0.0144 |
| Share female | 0.0129 | 0.0113 | 0.0066 |
| Mean age | 1.5828 | 1.0555 | 1.0876 |
| **Immigrants by residence 1 year ago** | | | |
| Share by origin | 0.0058 | | |
| Share female | 0.0636 | | |
| Mean age | 3.2037 | | |

## A.6 CONAPO and ENOE comparison

**Table A.11:** Comparison between CONAPO and ENOE data

| | **CONAPO**<br>Official | **ENOE**<br>Proposed |
|---|---|---|
| *Primary data* | From Mexico: censuses, intercensal survey, ENADID (demographic survey).<br>From USA: censuses, ACS | Household survey (5-quarter panel) |
| *Method* | Demographic estimations and models | Survey estimates |
| *Frequency* | Yearly | Yearly (quarterly option) |
| *Population* | Residents of Mexico | Sampled households |
| *Numerator* | Sum of migrant counts relative to a year ago | Sum of migrant counts relative to the household roster of the previous wave (previous quarter) |
| *Denominator* | Mid-year population | Weighted sum of quarterly exposure |

## A.7 Common Sample results

**Figure A.2:** Migration rates after adjusting for changes in timing of interview

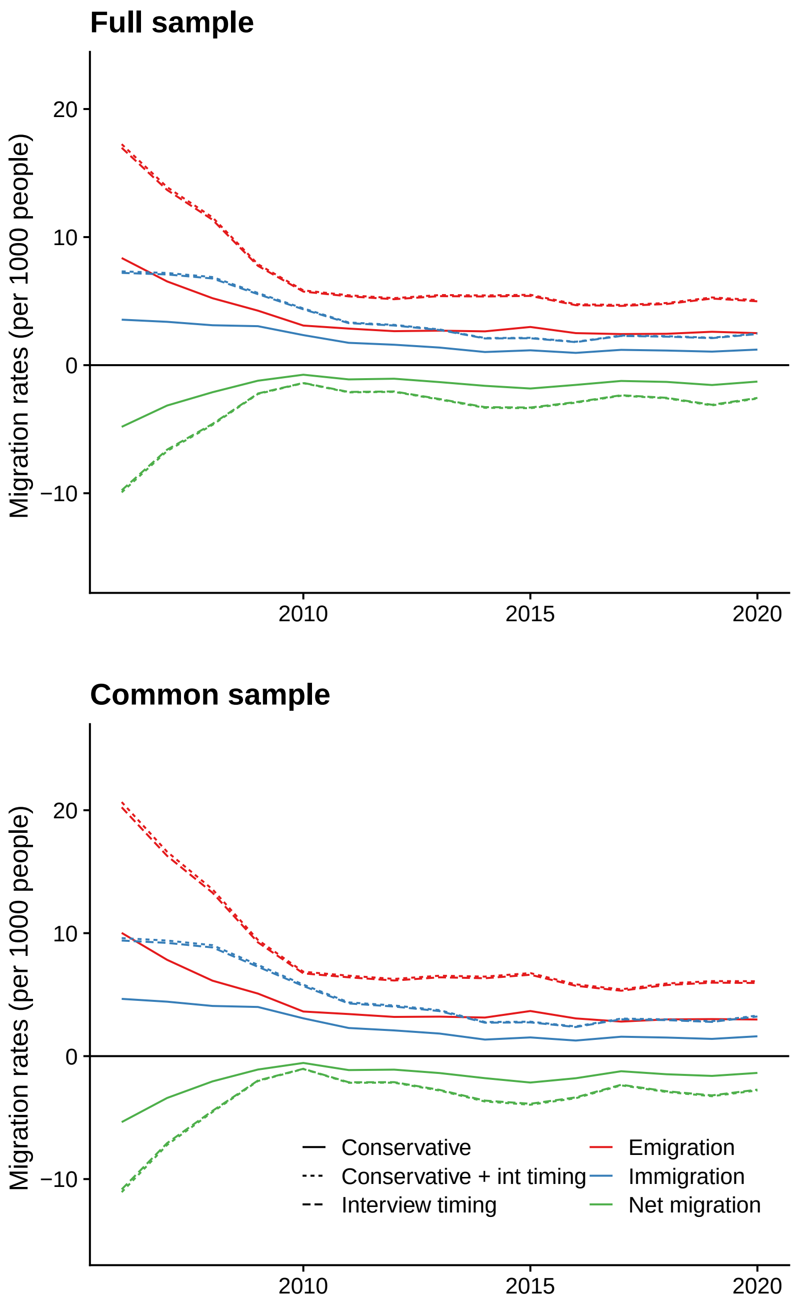


**Figure A.3:** Migration rates after adjusting for households that where all members migrated at once.

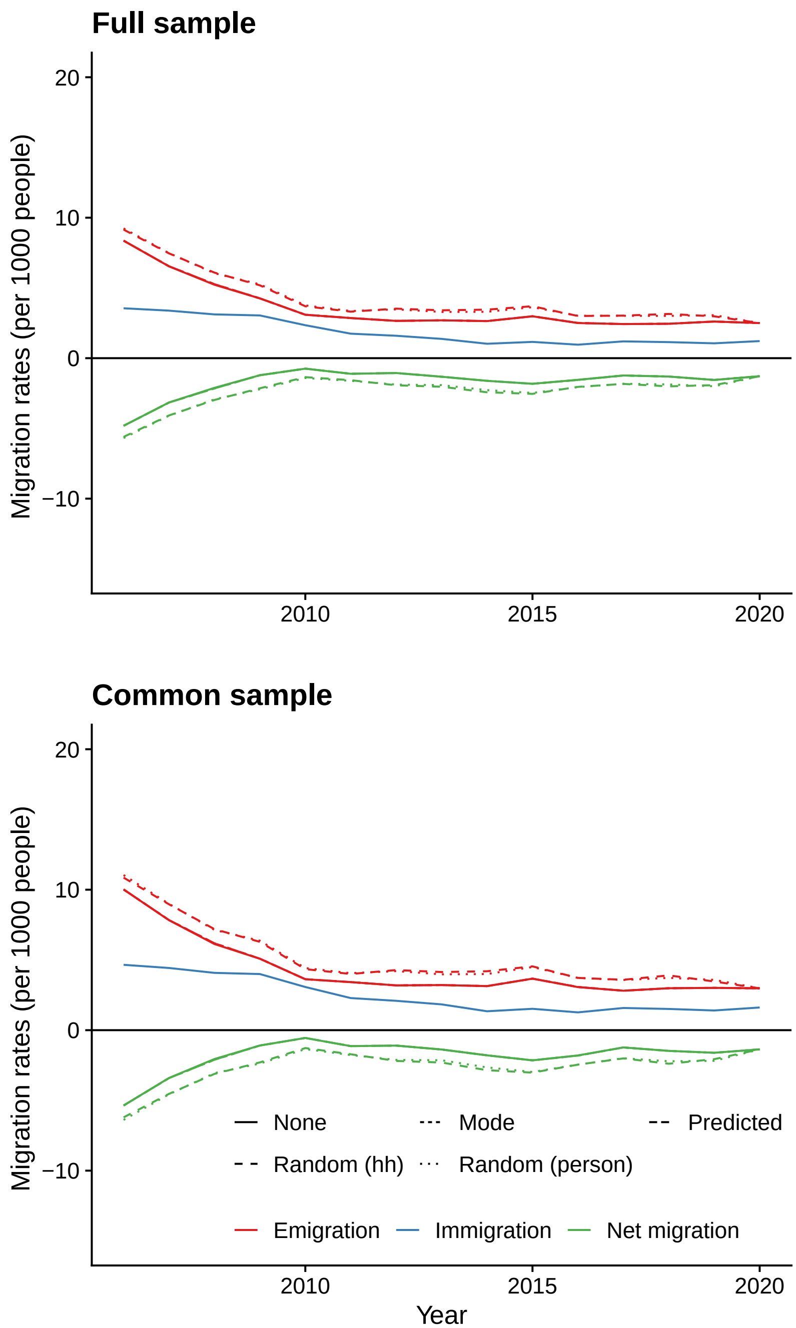
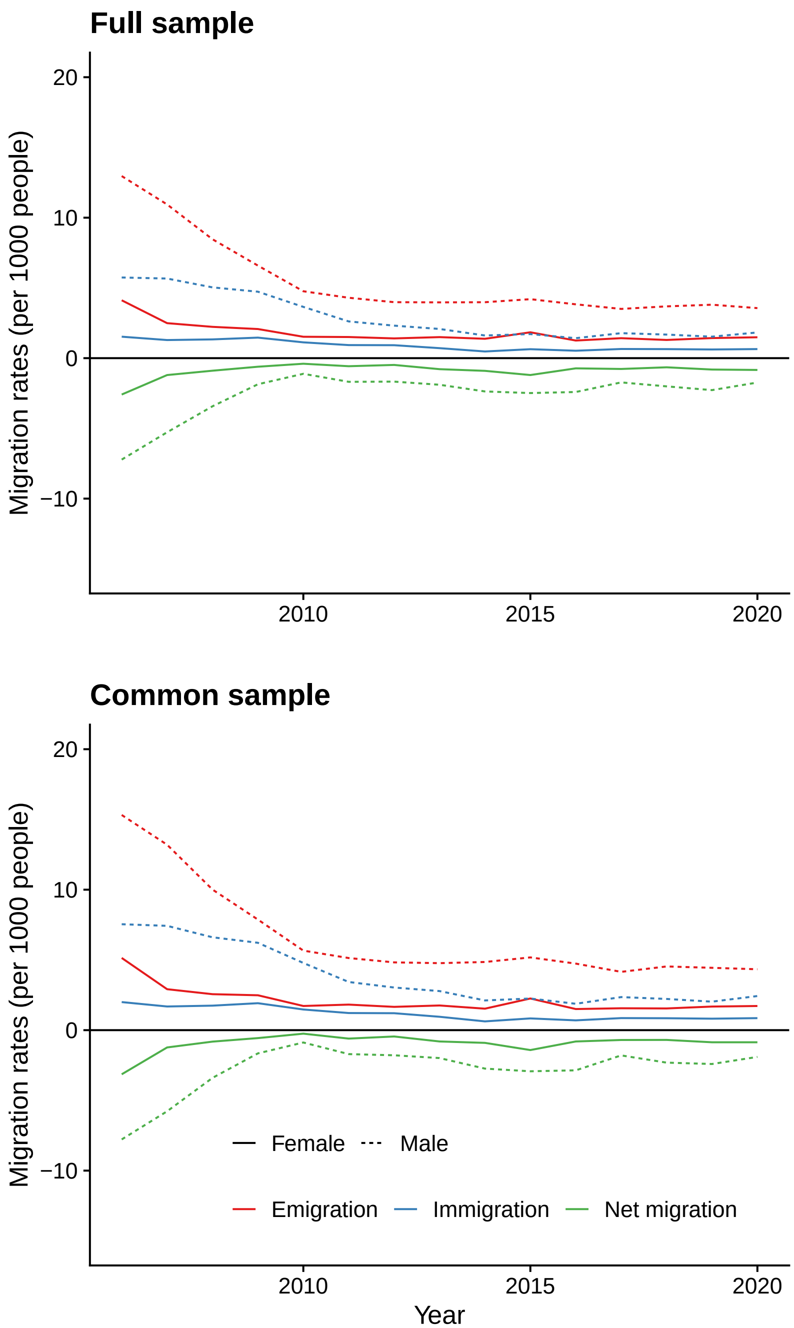


**Figure A.4:** Migration rates by sex over time



## A.8 Robustness of ENOE migration rates

### A.8.1 Timing of interview

ENOE documentation shows that the interviews do not occur at the same time in a quarter. Typically, interviews are first carried out to households close to any INEGI offices, which are mostly in large cities, and then they are conducted in more rural areas. As a result, households that are interviewed later in the quarter have a higher exposure to having one of its members be a migrant (because more time has passed in order to report them). Households that are interviewed early in the quarter are not able to report a migrant who may leave later in the quarter. These households will have to report the absent person in the next interview which is a quarter after the quarter of the event. Therefore, the timing of the interview can affect the quarter when the migrant was reported which when aggregated can affect the shape of the migration rate.

In light of this, I propose adjustments to the numerator and the denominator. Migrants that are reported within the first 2 weeks[1] of a quarter are moved a quarter earlier. For instance, if a household is interviewed on January 4th, 2008 and it reports a migrant, then I assign the migrant to 2007 Q4, rather than 2008 Q1. For the denominator, I use the timing of the interview to measure the share of days that a person spent in a given quarter. In equation 1.2, I assume that a resident of a household lived for a full quarter (0.25 years) and an absent or new resident lived for half a quarter (0.125 years). By using the time of the interview, we can have a more accurate exposure measure.

I focus on three measures of exposure. "Conservative" refers to exposure as defined in the previous paragraph. "Conservative and interview timing" refers to adjusting the "Conservative" exposure to the share of days spent in a quarter. "Interview timing" multiplies the share of days spent in a quarter by the full quarter length. For example, a household that was interviewed on February 1st, 2008 spent 32 days in the first quarter of 2008. Table A.12 shows an example of the exposure results[2].

**Table A.12:** Example of adjustment to exposure by the timing of interview

| Household Member | Conservative | Conservative + interview timing | Interview timing |
|---|---|---|---|
| Resident | 0.25 | $0.25 \times \frac{32}{90}$ | $0.25 \times \frac{32}{90}$ |
| Absent | 0.125 | $0.125 \times \frac{32}{90}$ | $0.25 \times \frac{32}{90}$ |
| New | 0.125 | $0.125 \times \frac{32}{90}$ | $0.25 \times \frac{32}{90}$ |

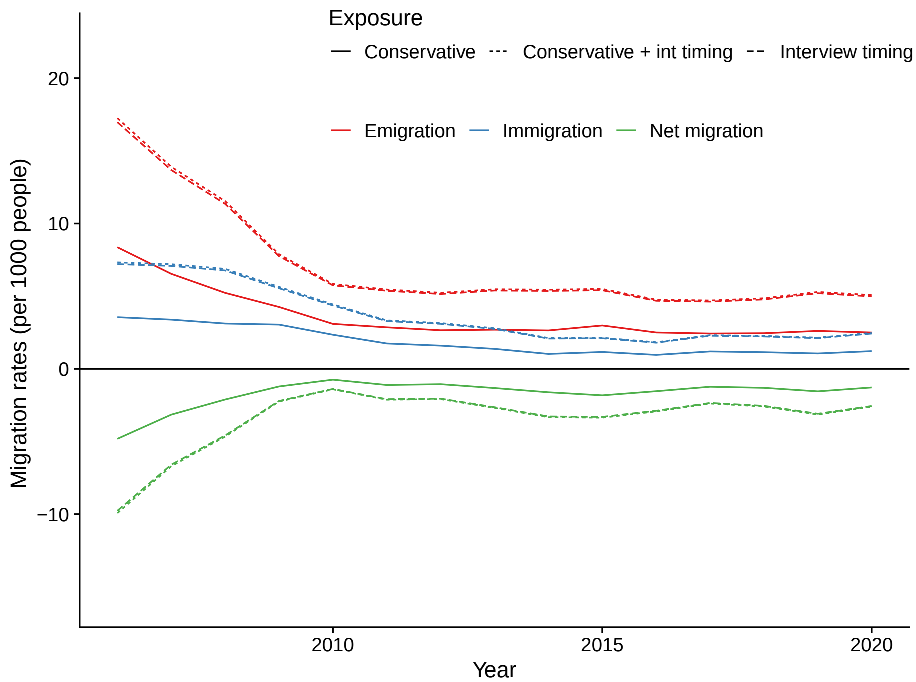
Figure A.5 shows that the migration rates that adjust for the timing of the interview are larger than the rates that use a conservative exposure. This is happening because the adjusted exposure is smaller than the conservative exposure. Except for the immigration rate, the adjusted rates are shifted versions (upwards) of the conservative measures. The adjusted immigration rate show a slight shift to the left relative to the conservative version.

[1] This was an arbitrary choice and it can be modified in the future.

[2] For simplicity, I omit multiplying by household weights but in the graphs, all rates include these survey weights.

Overall, adjusting the ENOE rates by the timing of the interview does not help explain why the ENOE rates are different than CONAPO's estimates. On the contrary, the difference would be larger.

**Figure A.5:** Migration rates after adjusting for changes in timing of interview.




### A.8.2 Sensitivity to household attrition

A key factor to identify a migrant in a longitudinal survey, as the ENOE, is that there is at least one member left in the household. Hamilton and Savinar (2015) estimate that about half of Mexican emigrants to the US were not reported in the MxFLS because of errors from misreporting (by existing household members) and from sampling (no one from household is left to report). Importantly, the undercount of emigrants is not random and affected women, children and receiving areas in the periphery of cities (Hamilton & Savinar, 2015). Using the ENOE up to 2006 Q4, Bertoli and Murard (2020) find that households that ever have a migrant are more likely to drop out of the survey than households without migrants. But this attrition is not completely explained by the migration of remaining members, rather they suggest that it is the result of merging with other households.

My conservative estimates only include migrants that were reported by someone in the household. However, we cannot directly observe migrants belonging to households where everyone left. To circumvent this problem, I use information on the completion of interviews. Every time INEGI interviewers visit a household, they record whether interviews were completed. Incomplete interviews can result from people denying to respond or from nobody being present at the time of the visit. For my purposes, interviewers can mark incomplete interviews because the "household moved away"[3]. From this, I can identify whole-household migrants, add them to the data, and estimate migration rates. I assume that the absent household is composed by everyone from the roster of the previous quarter. As a result, I can add about 13,000 person-quarter observations to the data where at least one member remained to answer the survey. These observations are usually discarded as their interview was incomplete.

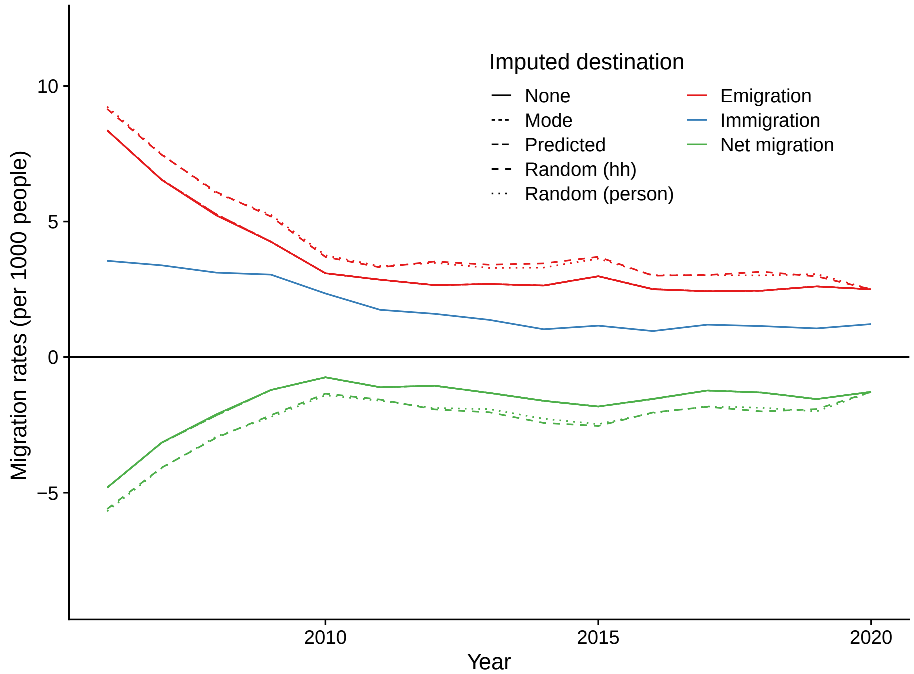
The next step was inferring the destination of these whole-household migrants since it is not recorded. I try 4 ways to impute the destination of the household. First, I use the modal destination among all migrants of the household before the household left the sample. Second, I estimate a multinomial logistic model to predict the destination (within the state, to another state, to another country) of the absent household. As a training and testing sample, I use observations of households that ever had a migrant. The features that I include are year, geographic location, household composition by gender and age structure, and presence of migrants in the past. Then, the model is selected based on the highest accuracy from a 4-fold cross-validation process. Surprisingly, the testing accuracy was about 99%. This is a bit misleading because the model is accurately predicting the most common destination (within state migration). Unfortunately, the model only predicts a very small share of households that migrate internationally. Since the unit of analysis is a household, I assume that everyone in a given migrant household has the same destination. The third alternative is to randomly assign people within the household to any of the 3 possible destinations. Finally, another alternative is to assign everyone in the household the same destination as the random destination (from the third alternative) of the oldest member of the household. Here, I assume that migration of families is a household decision.

Figure A.6 shows the differences between the types of adjustments. By construction, immigration has no adjustment. In terms of the emigration rates, when the destination is imputed as the mode or predicted from a model, the rates are very similar to those when there is no imputation. This is because international migration is not a common event relative to internal migration. The random imputations as independent people or households suggest some upper-limit of what the migration rates could be if international migration was as likely as internal migration.

The purpose of sections A.8.1 and A.8.2 was to understand if the reasons suggested by existing literature may be driving the difference between migration rates from figure 1.4. However, estimates in figure A.5 and figure A.6 show little evidence that these adjustments help to reduce the gap between ENOE and CONAPO rates. Instead of finding ways to make the ENOE closer to CONAPO model estimates, ENOE rates may be thought of as an upper limit to the true migration rate. Researchers may consider using the ENOE to follow changes in trends rather than tracking magnitudes.

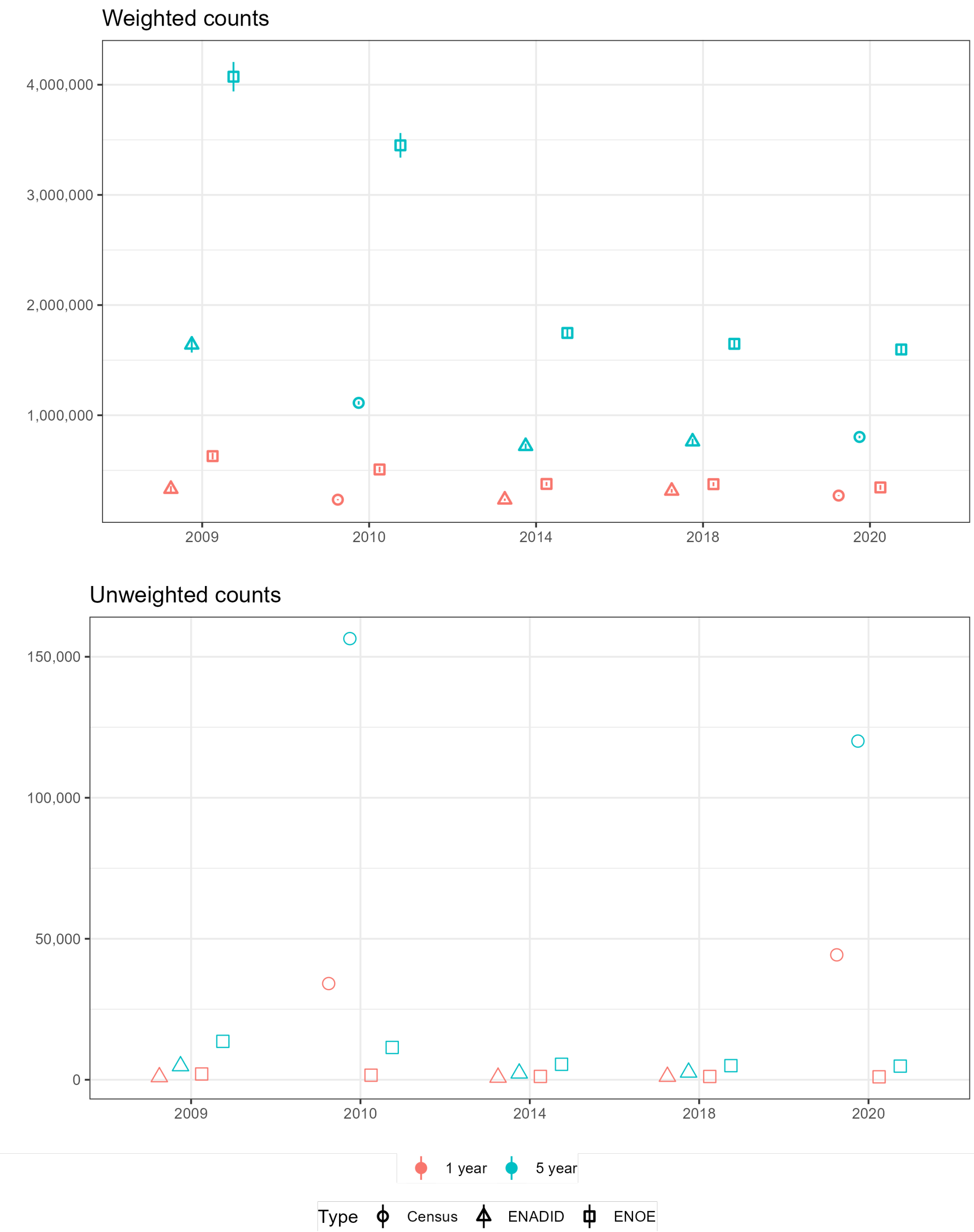
[3]From my understanding, interviewers typically ask neighbors for additional information on the whereabouts of members from the sampled household.

**Figure A.6:** Migration rates after adjusting for households that where all members migrated at once.



## A.9 Emigrant counts across data

**Figure A.7:** ENOE is not meant for calculating counts of migrants.



# Appendix B

# Appendix for Chapter 2

## B.1 Migrant and Non-Migrant Categories in the ENOE

### B.1.1 Identifying Whole-household Migration

Initially, we classified observations that were not present as "Absent". However, this depends on having someone left in the household who can report on those who left. There are cases where all members of the household drop out of the ENOE. Since there is no one left in the household to interview, it is uncertain what happened to them. However, the ENOE interviewers collect as much information as possible from the surroundings of the household to understand why there is no one in the household to interview. To ensure a high response rate, INEGI interviewers visit the sampled dwelling up to five times (Instituto Nacional de Estadística y Geografía, 2007, p. 70) if there was nobody qualified to answer the survey on the first visit. Interviewers may reach out to neighbors to obtain any information about the occupants of the dwelling and, together with a visual evaluation of the household, they determine if an interview will not be carried out. If they cannot contact a household member within five visits in the same quarter, then the interview is marked as unsuccessful.

We exploit this additional information to identify households that may have migrated together. For all people in households with four or fewer interviews, we look at the next quarter interview status and determine if the people belong to a household that most likely moved together, or if they are likely non-migrants. For people to be classified as migrants the status of their next interview visit was "Household moved away". People could also be classified as possible migrants if their next interview visit was: "Ready-to-use dwelling but uninhabited," "Non-functional/deteriorating dwelling," "Temporarily not used as a dwelling (office, storage, etc)," "Demolished," "Changed location (mobile dwelling)," "Permanently not used as a dwelling (office, storage, etc)," "Other reasons for dwelling not being available." In all of these cases, we believe that people may have left because in the last available interview, their dwelling was occupied and then there was a sudden change in dwelling status the next period.

Finally, some observations could not be classified as migrants (or non-migrants) because they lived in households that could not be interviewed in the next quarter. The reasons for no interview were: "Nobody at time of interview," "Temporarily absent (work, vacation, illness)," "Denied providing information," "Unqualified respondent," "Other reasons even if the dwelling was habitable," "Temporary-use dwelling (vacation home, crop seasons, etc)," "Interviewed suspended". These labels suggest some randomness in the absence of people so it is hard to classify them as temporarily being absent or being migrants. Overall, households can be classified as migrants, possible migrants, or cannot be classified as migrants.

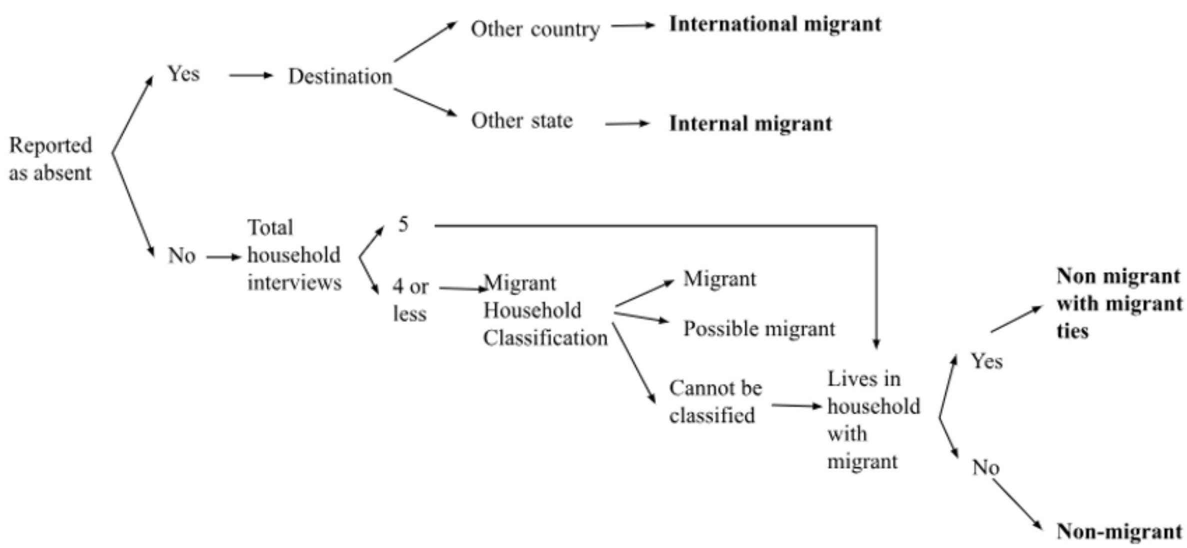
### B.1.2 Migrants in households

In addition to the household categories, we can also tag any households that have ever had an internal or an international migrant. People who were not absent during the interviewing window may live in a household with a migrant and are labeled non-migrant with migrant ties.

### B.1.3 Migrant definitions

Based on the classifications of household status and migrants in households, we summarize the definition of non-migrants and migrants in the following graph.

**Figure B.1:** International migrant categories from the ENOE




A migrant is anyone who is reported as absent by remaining household members and who has a reported destination. If the destination is "Another country", then the person is an international migrant. An internal migrant is someone who went to "Another state".

A non-migrant is 1) someone who at the moment of the fifth interview was not reported as "Absent" by a household member or 2) someone who at the fourth or earlier interview was not reported as "Absent" by a household member, but is part of a household that was not interviewed at later quarters and classified as "Cannot be classified as migrants".

Table B.1 shows the size of each group. Similar to Table 1 in the original paper, most observations are non-migrants, and international migrants are a small share (0.4%) of the ENOE. However, non-migrants with ties are 14.7% of the ENOE, which suggests that many people live with people who are mobile (internally or internationally). Throughout the analysis, we drop any observations where the migrant household classification is "Migrant" or "Possible migrant," which is about 1.7% of the collapsed ENOE.

**Table B.1:** Composition of respondents by complete preparations and migration categories

| | | | Prepares | | % that prepares (by row) |
|---|---|---|---|---|---|
| Category | Observations | all obs. | No | Yes | |
| Non-migrant | 3,242,183 | 81.6 | 3,229,657 | 12,526 | 0.4 |
| International migrant | 17,365 | 0.4 | 16,658 | 707 | 4.1 |
| Non migrant with ties | 584,159 | 14.7 | 581,686 | 2,473 | 0.4 |
| Internal migrant | 52,695 | 1.3 | 52,393 | 302 | 0.6 |
| Migrant | 3,687 | 0.1 | 3,680 | 7 | 0.2 |
| Possible migrant | 72,532 | 1.8 | 72,371 | 161 | 0.2 |
| Total | 3,972,621 | 100 | 3,956,445 | 16,176 | 6 |

## B.2 Variable description

**Table B.2:** Description of variables

| Variable | Description | Categories | Reference group in regressions |
|---|---|---|---|
| Sex | Sex are reported to interviewers. | Male, Female | Female |
| Age groups | Age binned into 10-year age groups from 10 to 100. First age group, 0-10, not included because outside of analytical sample | [10,20)-[90,100] | [20,30) |
| Education | Current level of education of respondents. Does not necessarily indicate completed education or years in school | No education, elementary (includes pre-school), middle school, high school, technical career, college and graduate studies. | High school |
| Regions in Mexico | States divided into regions based on Durand (2017, p.28): the Historic migrant-sending states (Aguascalientes, Colima, Durango, Guanajuato, Jalisco, Michoacán, Nayarit, San Luis Potosí, Zacatecas); states along the North (Baja California, Baja California Sur, Sinaloa, Sonora, Chihuahua, Coahuila, Nuevo León, Tamaulipas) border, states in the Center (Mexico City, Hidalgo, Querétaro, State of México, Morelos, Puebla, Tlaxcala, Guerrero) of Mexico and states in the Southeast (Chiapas, Tabasco, Quintana Roo, Campeche, Yucatán, Veracruz, Oaxaca) of Mexico. | Historic-migrant sending, North, Center, Southeast | Historic |
| Year | Year of interview, binned by 3 years | [2006,2008), (2008,2011], (2011,2014], (2014,2017], (2017,2019] | [2006,2008) |
| Urbanicity | Location is categorized as urban or rural by INEGI | Urban, rural | Rural |

*Continued on next page*

**Table B.2:** Description of variables

| Variable | Description | Categories | Reference group in regressions |
|---|---|---|---|
| Place of birth | Place of birth of respondents where rest of the world contains many nationalities, but fewer counts than the rest of foreign nationalities. We do not assume that place of birth is a proxy for country of citizenship. | Mexico, Guatemala, Spain, USA, rest of the world | Mexico |
| Education | Current education level of respondents and does not represent 1) completed education or 2) completed level. We include levels of education instead of years because of the non-linearities of increasing education. Elementary school contains preschool. Graduate studies encompasses Master's and PhD degrees. Trade school includes teacher degree and a technical careers. | None, elementary school, middle school, high school, trade school, college and graduate studies | High school |
| Kinship | The ENOE records kinship relative to the household head. There are numerous categories but we synthesize them to 6. | Household head (HH), spouse of partner of HH, child of HH, grandchild of HH, daughter in-law or son in-law and remaining categories | HH |
| Partnership | A value of 1 indicates that a person is married or is living with their partner. A value of 0 indicates that a person is separated or divorced or widowed or single | Has partner, no partner | No partner |
| Share children (%) | Share of household members in a given quarter who are under the age of 18 | | |
| Share elderly (%) | Share of household members in a given quarter who are over the age of 75 | | |

*Continued on next page*

**Table B.2:** Description of variables

| Variable | Description | Categories | Reference group in regressions |
|---|---|---|---|
| Labor force status | We use categories of the labor force status as defined by Instituto Nacional de Estadística y Geografía (2007, p.14-17). The labor force refers to the group of people that are willing and able to work, who are either employed (*"Población ocupada"*) or unemployed (*"Población desocupada"*). Those who are unemployed are actively seeking for a job. The population outside of the labor force are those who do not offer labor but instead depend on monetary or non monetary transfers. Some examples include students, and people who are retired. People who are available and out of the labor force are interested in working but not actively looking for a job (or working). Those who are unavailable and out of the labor force are not working, are not interested in work or who cannot work. Not applicable refers to people aged 14 and less who are not legally allowed to work. | Not applicable, unemployed, employed, available, unavailable | Employed |
| Household receives remittances | Takes value of one if any member in the household receives any remittances (from abroad, from another state, or from within a state) in a quarter. | Any household member receives/ doesn't receive | No member of household receives remittances |
| Remittances received by states | Remittances in real dollars that were received by the state of residence of the respondent in a given quarter. We use demeaned and standardized values. Source: Banxico (Remittances per state, Balance of Payments) | | |
| Wage differential | Wages of workers in the manufacturing industry (US dollars/hour) in Mexico and the US (Source: INEGI's Economic Information Database). Monthly wages are averaged over quarters and then we take the difference between the US wages and the Mexican wages. We use demeaned and standardized values. | | |

*Continued on next page*

**Table B.2:** Description of variables

| Variable | Description | Categories | Reference group in regressions |
|---|---|---|---|
| Distance to border | Distance (kilometers) from the centroid of the respondents municipio to the closest point of entry along the US-Mexico border. We use Open Street Maps to obtain the shortest driving distance between the coordinates. Values are demeaned and standardized. | | |
| Unemployment rate (USA) | We obtain the average quarterly unemployment rate in the USA (Source: FRED). We use national rates as we do not assume specific destinations of migrants. We use demeaned and standardized values. | | |
| Employment rates (Mexico) | State-specific employment rates from INEGI in a given quarter. We use demeaned and standardized values. | | |

## B.3 Descriptive statistics

**Table B.3:** Descriptive statistics across migrant-preparation categories

| | Non-migrants | | | International migrants | | | Non-migrants with ties | | | Internal migrants | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Prepares? | Yes | No | | Yes | No | | Yes | No | | Yes | No | |
| Age | 34.5 | 37.2 | *** | 31.8 | 31.8 | | 34.1 | 37.5 | *** | 29.85 | 29.19 | |
| % Female | 0.24 | 0.52 | *** | 0.07 | 0.26 | *** | 0.29 | 0.54 | *** | 0.17 | 0.41 | *** |
| % Rural | 0.46 | 0.38 | *** | 0.71 | 0.59 | *** | 0.47 | 0.42 | *** | 0.47 | 0.44 | |
| **Region in Mexico** | | | | | | | | | | | | |
| North | 0.24 | 0.26 | *** | 0.2 | 0.22 | | 0.24 | 0.23 | | 0.28 | 0.28 | |
| Historic | 0.32 | 0.29 | *** | 0.5 | 0.45 | ** | 0.33 | 0.3 | *** | 0.3 | 0.25 | ** |
| Center | 0.29 | 0.24 | *** | 0.22 | 0.22 | | 0.3 | 0.25 | *** | 0.23 | 0.2 | |
| Southeast | 0.15 | 0.22 | *** | 0.08 | 0.1 | ** | 0.14 | 0.23 | *** | 0.19 | 0.27 | *** |
| **Birthplace** | | | | | | | | | | | | |
| Mexico | 0.98 | 0.99 | *** | 0.97 | 0.93 | *** | 0.98 | 1 | *** | 0.98 | 0.99 | ** |
| USA | 0 | 0 | ** | 0.01 | 0.02 | *** | 0 | 0 | ** | 0 | 0 | |
| Rest of the world | 0.02 | 0 | *** | 0.03 | 0.05 | ** | 0.02 | 0 | *** | 0.02 | 0 | *** |
| **Relationship to household head** | | | | | | | | | | | | |
| Household head | 0.54 | 0.36 | *** | 0.46 | 0.3 | *** | 0.43 | 0.34 | *** | 0.25 | 0.14 | *** |
| Spouse/Partner | 0.1 | 0.24 | *** | 0.08 | 0.09 | | 0.09 | 0.19 | *** | 0.02 | 0.06 | *** |
| Child | 0.3 | 0.31 | *** | 0.37 | 0.46 | *** | 0.39 | 0.35 | *** | 0.49 | 0.48 | |
| Grandchild | 0.02 | 0.02 | | 0.03 | 0.04 | * | 0.02 | 0.03 | * | 0.05 | 0.05 | |
| Daughter/Son in-law | 0.01 | 0.02 | *** | 0.02 | 0.03 | | 0.02 | 0.03 | ** | 0.03 | 0.05 | * |
| Other | 0.03 | 0.05 | *** | 0.04 | 0.08 | *** | 0.05 | 0.07 | *** | 0.16 | 0.22 | *** |
| **Household composition** | | | | | | | | | | | | |
| % Children (< 18) | 0.14 | 0.16 | *** | 0.16 | 0.16 | | 0.15 | 0.16 | *** | 0.12 | 0.14 | * |
| % Elderly (> 65) | 0.02 | 0.04 | *** | 0.01 | 0.02 | *** | 0.02 | 0.02 | *** | 0.02 | 0.02 | |
| **Current education** | | | | | | | | | | | | |
| None | 0.02 | 0.05 | *** | 0.02 | 0.03 | * | 0.03 | 0.06 | *** | 0.02 | 0.03 | |
| Elementary | 0.21 | 0.28 | *** | 0.29 | 0.29 | | 0.24 | 0.32 | *** | 0.19 | 0.19 | |
| Middle school | 0.3 | 0.28 | *** | 0.38 | 0.33 | *** | 0.32 | 0.29 | *** | 0.31 | 0.29 | |
| High school | 0.21 | 0.17 | *** | 0.19 | 0.2 | | 0.2 | 0.15 | *** | 0.19 | 0.23 | |
| Trade school | 0.05 | 0.06 | *** | 0.03 | 0.03 | | 0.05 | 0.05 | | 0.02 | 0.03 | |
| College | 0.21 | 0.16 | *** | 0.08 | 0.13 | *** | 0.17 | 0.12 | *** | 0.24 | 0.22 | |
| Graduate studies | 0.02 | 0.01 | *** | 0.01 | 0.01 | * | 0.02 | 0.01 | *** | 0.04 | 0.01 | *** |
| **Labor force status** | | | | | | | | | | | | |
| Employed | 0.03 | 0.06 | *** | 0.02 | 0.06 | *** | 0.04 | 0.07 | *** | 0.02 | 0.07 | *** |
| Unemployed | 0.09 | 0.37 | *** | 0.1 | 0.25 | *** | 0.1 | 0.36 | *** | 0.08 | 0.29 | *** |
| Available | 0.13 | 0.02 | *** | 0.27 | 0.06 | *** | 0.15 | 0.03 | *** | 0.29 | 0.07 | *** |
| Unavailable | 0.75 | 0.54 | *** | 0.61 | 0.64 | | 0.72 | 0.54 | *** | 0.62 | 0.58 | |
| **Reason for migration** | | | | | | | | | | | | |
| Work | | | | 0.93 | 0.73 | *** | | | | 0.71 | 0.5 | *** |
| Education | | | | 0.02 | 0.08 | *** | | | | 0.06 | 0.11 | *** |
| Partnership | | | | 0.01 | 0.03 | *** | | | | 0.05 | 0.04 | |
| Separation | | | | 0 | 0.01 | * | | | | 0.03 | 0.03 | |
| Health issues | | | | 0 | 0.01 | | | | | 0 | 0.01 | |
| Family reunification | | | | 0.02 | 0.1 | *** | | | | 0.1 | 0.22 | *** |
| Safety issues | | | | 0 | 0 | | | | | 0 | 0 | |
| Other | | | | 0.02 | 0.05 | *** | | | | 0.05 | 0.08 | * |

Note: except for age and the household composition all variables are dichotomous. As such, the values in the table represent shares within each bolded group by each column. Stars suggest results from chi-squared tests on the difference in the share (between preparation=no and preparation=yes) where we reject the null hypothesis at 99% (***), 95% (**) and 90% (*).

## B.4 Data comparison with alternative sources on migrant aspirations in Mexico

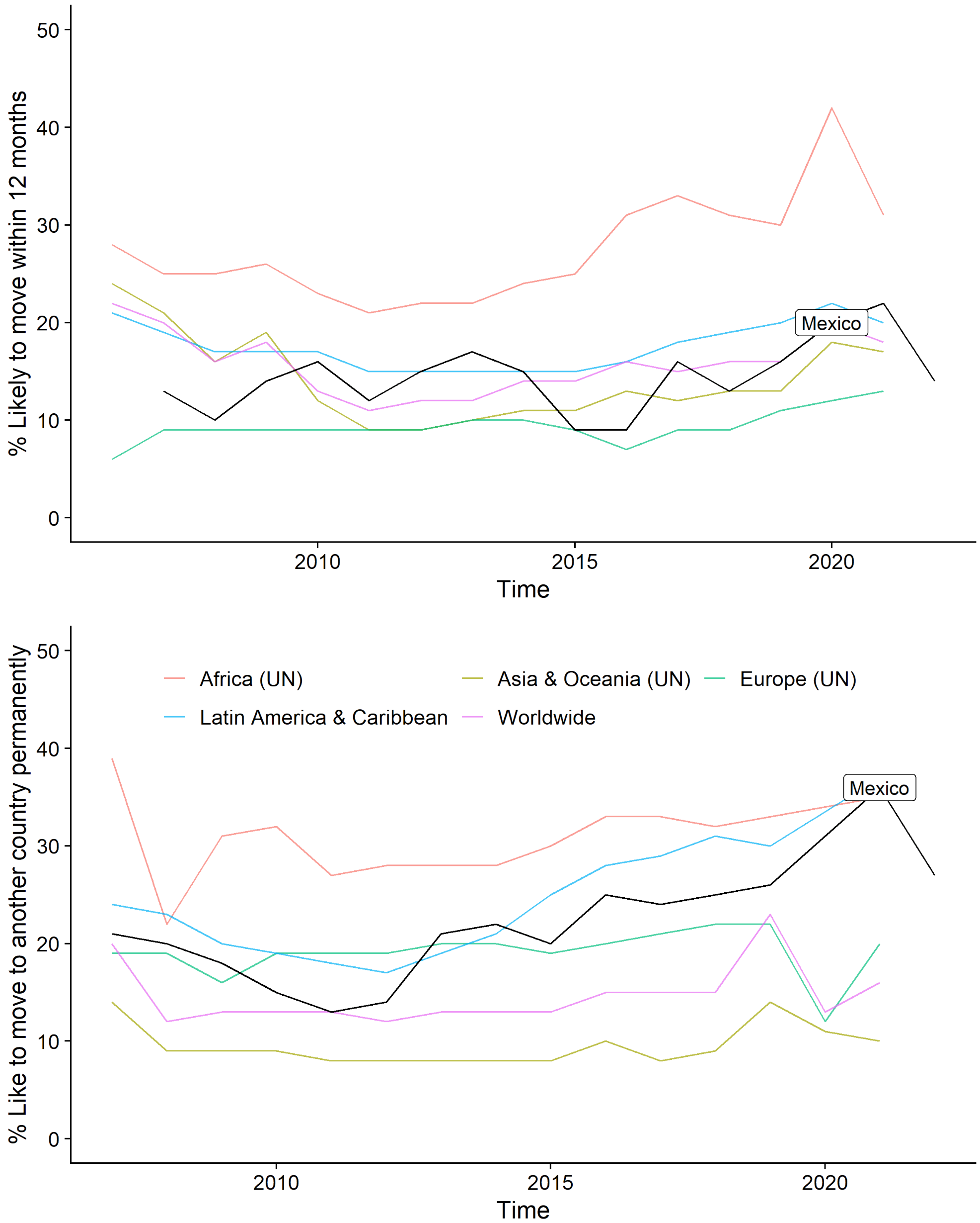
Despite the importance of this planning or preparatory phase, motivational/aspirational dimensions of migration have received the most attention. This is especially true for quantitative analyses. To a large extent, this is due to the characteristics of the existing survey data. As stressed by Carling and Schewel (2018), survey questions determine the dimensions of the pre-migration dynamics that we can analyze. Per these authors, most existing surveys, like the Gallup World Poll or the Latinobarometer, have focused on one, or at best a few, measures of migration aspirations or intentions. Furthermore, these queries tend to be based on ideal or hypothetical migration scenarios, for which no or little preparation has been undertaken by the respondents.

We put our values from Table 2.1 in the original paper into context using available data from other large surveys that include Mexico. Creighton (2013) uses the Mexican Family Life Survey (MxFLS), and his Table 4 shows that the majority of respondents do not have intentions in the first wave of the MxFLS. However, the shares of people with intentions are much larger than our estimates. Estimates from the Gallup World Poll (GWP) in figure B.2 show that the share of people in Mexico that are likely to move away within the next 12 months has oscillated between 10% and 20% between 1996 and 2020. The share of GWP respondents in Mexico who would like to move permanently abroad is almost double that of the former question. Relative to other regions, Mexico is not an outlier. Finally, the Americas Barometer asks "Have you and your family thought about the tangible possibility of moving to another country?" Figure B.3 shows that between 15% and 35% of respondents would consider migrating.

There are two main reasons why these values differ from our Table 2.1. First, the questions are not strictly comparable. As explained in section 2.3, our question looks at preparations to migrate, while questions from GWP, MxFLS and the Latinobarometer look at intentions to migrate, which is, as we have discussed, a previous step to planning migration. Following Kley (2011), those who are planning to migrate have developed intentions to migrate, by definition. But those with intentions to migrate have not necessarily begun to plan their migration. Therefore, we should at least expect the shares of respondents with concrete plans to migrate to be a subset of the larger group of people with intentions.

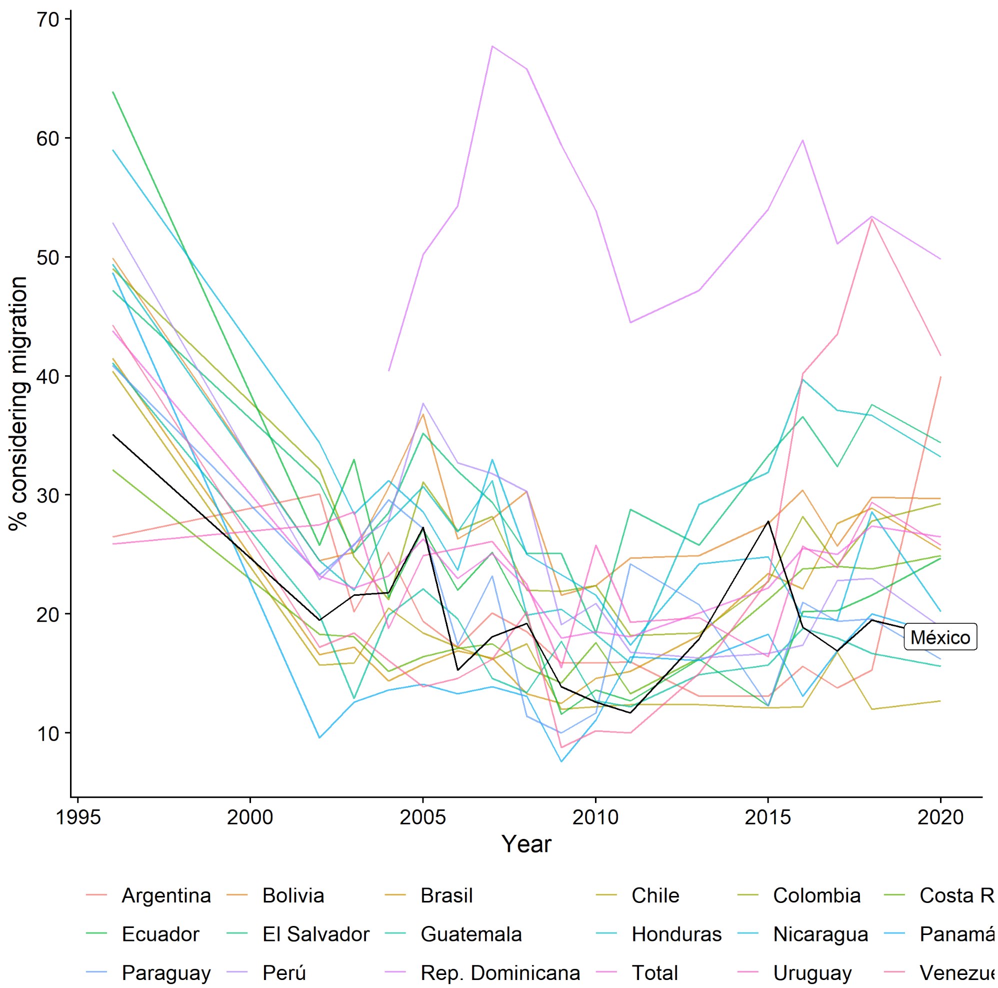
A second reason for the difference is due to how the ENOE is collected. The interviewer's manual states that the interviewer should interview each person from the sampled household. However, when some members are absent during a given day, interviewers can rely on the answers of an 'adequate informant'. This person is 'a person who is a resident of the sampled household and who must know the information of the remaining household members. The adequate informant may be the household head or another member who is 15 years or older" (Instituto Nacional de Estadística y Geografía, 2009, p. 13). To the extent that the adequate informant does not know about the preparations of the household members, then we can expect an undercount of cases. Unfortunately, we cannot obtain information on whether the interviewer talked only to the adequate respondent or to each household member.

**Figure B.2:** Insights on intentions from Gallup World Poll.




Source: data downloaded from Gallup Analytics with access from UC Berkeley library.

**Figure B.3:** Insights on intentions from Latinobarometro.

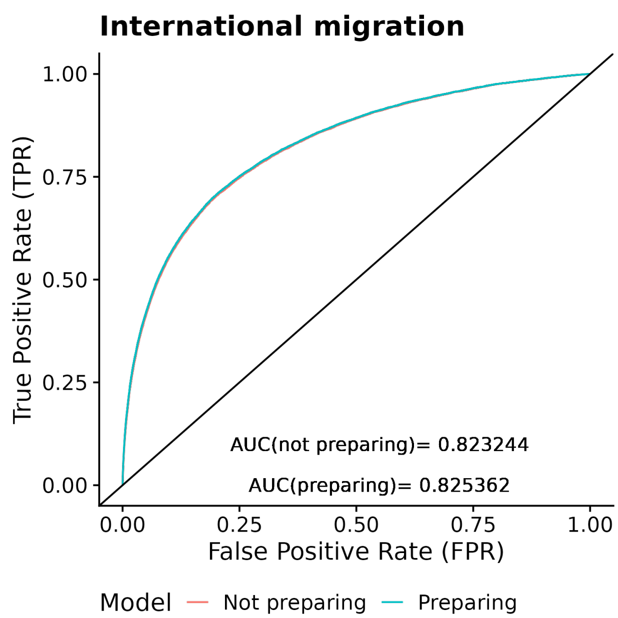



Note: Latinobarometer asks "Have you and your family thought in the tangible possibility of moving to another country?". Source: online analysis at https://www.latinobarometro.org/latOnline.jsp.

## B.5 Do preparations predict migration?

The Receiver Operating Characteristic (ROC) is a plot of the True Positive Rate (TPR) (number of correct predictions of being a migrant / number of true migrant cases) against the False Positive Rate (FPR) (number of incorrect predictions of being a migrant / number of cases of not being a migrant). Ideally, we want a ROC with high values of TPR but low values of FPR in order to have more confidence about correctly predicting migration. We calculate the areas under the ROCs (called the Area Under the Curve or AUC). A higher AUC indicates higher predictive power of a model. Models that excel in accurately predicting outcomes will have a ROC that is vertical at FPR = 0 and horizontal at TPR=1 (like square). The ROC is very similar between the model with and without intentions for both types of migrants. This is shown by how both lines are practically superposed (Figure B.4). The similar AUCs indicate that the models are equally good at predicting migration. We also include the odds ratio of these regression models, which suggests that there is a strong correlation between preparing and being an international migrant, even when we include determinants of migration. To assess the model's selection we turn to the Akaike Information Criterion (AIC). Model in column (3) shows a slightly lower AIC, which indicates a better fit of the model.

**Figure B.4:** Evaluation of models predicting being an international migrant



| | Dependent variable: | | |
|---|---|---|---|
| | International migrant (0/1) | | |
| | (1) | (2) | (3) |
| Intercept | 0.004*** | 0.002*** | 0.002*** |
| | (0.004,0.004) | (0.002,0.003) | (0.002,0.003) |
| Preparations=1 | 10.785*** | | 4.353*** |
| | (9.986,11.647) | | (4.003,4.734) |
| Female=1 | | 0.321*** | 0.328*** |
| | | (0.308,0.334) | (0.315,0.342) |
| Age | | 1.127*** | 1.124*** |
| | | (1.119,1.134) | (1.116,1.131) |
| Age squared | | 0.998*** | 0.998*** |
| | | (0.998,0.998) | (0.998,0.999) |
| **Region in Mexico (ref: Historic migrant-sending states)** | | | |
| North | | 0.443*** | 0.441*** |
| | | (0.422,0.466) | (0.420,0.464) |
| Center | | 0.616*** | 0.616*** |
| | | (0.592,0.641) | (0.591,0.641) |
| Southeast | | 0.386*** | 0.386*** |
| | | (0.362,0.411) | (0.363,0.412) |
| **Place of birth (ref: Mexico)** | | | |
| USA | | 13.118*** | 12.315*** |
| | | (12.130,14.187) | (11.377,13.330) |
| Rest of the world | | 12.591*** | 12.606*** |
| | | (11.186,14.171) | (11.199,14.190) |
| **Urban=1** | | 0.436*** | 0.442*** |
| | | (0.422,0.451) | (0.428,0.457) |
| **Current education (ref: High school)** | | | |
| None | | 0.658*** | 0.665*** |
| | | (0.595,0.727) | (0.602,0.735) |
| Elementary | | 0.952** | 0.958* |
| | | (0.908,0.998) | (0.914,1.004) |
| Middle school | | 1.018 | 1.020 |
| | | (0.974,1.063) | (0.976,1.066) |
| Trade school | | 0.636*** | 0.640*** |
| | | (0.575,0.704) | (0.578,0.708) |
| College | | 0.759*** | 0.765*** |
| | | (0.718,0.802) | (0.723,0.808) |
| Graduate studies | | 0.700*** | 0.702*** |
| | | (0.584,0.839) | (0.586,0.841) |
| **Labor force status (ref: Employed)** | | | |
| Unemployed | | 1.671*** | 1.540*** |
| | | (1.566,1.783) | (1.442,1.644) |
| Available | | 0.699*** | 0.707*** |
| | | (0.651,0.751) | (0.658,0.759) |

| | | | |
|---|---|---|---|
| Unavailable | | 0.621*** | 0.631*** |
| | | (0.593,0.651) | (0.602,0.661) |
| **Has partner=1** | | 1.777*** | 1.765*** |
| | | (1.694,1.863) | (1.683,1.851) |
| **Relationship to household head (ref: head of household)** | | | |
| Spouse/Partner | | 0.727*** | 0.733*** |
| | | (0.680,0.777) | (0.686,0.783) |
| Child | | 2.683*** | 2.716*** |
| | | (2.541,2.834) | (2.571,2.869) |
| Grandchild | | 2.325*** | 2.368*** |
| | | (2.094,2.581) | (2.133,2.629) |
| Daughter/Son in-law | | 2.020*** | 2.059*** |
| | | (1.857,2.199) | (1.891,2.241) |
| Other | | 3.611*** | 3.671*** |
| | | (3.373,3.867) | (3.429,3.932) |
| **Income quartile (ref: lowest 2 quartile/ 0 income)** | | | |
| Income Q3 | | 0.570*** | 0.580*** |
| | | (0.523,0.622) | (0.531,0.632) |
| Income Q4 | | 0.502*** | 0.503*** |
| | | (0.413,0.610) | (0.414,0.612) |
| **Share of household members** | | | |
| Children | | 0.561*** | 0.559*** |
| | | (0.537,0.585) | (0.535,0.583) |
| Elderly (> 65) | | 0.474*** | 0.483*** |
| | | (0.452,0.498) | (0.459,0.507) |
| **Remittances** | | | |
| Household receives remittances=1 | | 3.387*** | 3.351*** |
| | | (3.274,3.504) | (3.239,3.467) |
| Real remittances received (state) | | 1.124*** | 1.121*** |
| | | (1.099,1.150) | (1.097,1.147) |
| **Macroeconomic trends** | | | |
| US-Mex wage difference | | 1.031 | 1.044 |
| | | (0.795,1.338) | (0.805,1.356) |
| Unemployment rate (US) | | 0.986 | 0.986 |
| | | (0.891,1.091) | (0.891,1.091) |
| Employment rate (Mex) | | 0.983 | 0.986 |
| | | (0.960,1.007) | (0.962,1.010) |
| Distance to border | | 0.764*** | 0.769*** |
| | | (0.743,0.786) | (0.748,0.791) |
| Year | No | No | No |
| Quarter | No | No | No |
| Observations | 3,843,707 | 3,843,679 | 3,843,679 |
| Log Likelihood | -110,077.800 | -95,231.440 | -94,798.830 |
| Akaike Inf. Crit. | 220,159.600 | 190,564.900 | 189,701.700 |
| *Note:* | | | $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ |

## B.6 Event study full results

**Table B.4:** Event study results for the probability of ever being employed

| | Ever being employed = 1 (being unemployed or out of labor force =0) | | | |
|---|---|---|---|---|
| | Non migrant | International migrant | Non migrant with ties | Internal migrant |
| Model: | (1) | (2) | (3) | (4) |
| Quarters since event (ref = -1) | | | | |
| -4 | 0.021** | | -0.008 | |
| | (0.010) | | (0.023) | |
| -3 | 0.012* | 0.011 | -0.001 | -0.130 |
| | (0.007) | (0.065) | (0.015) | (0.096) |
| -2 | 0.009 | 0.023 | 0.027** | -0.029 |
| | (0.006) | (0.032) | (0.012) | (0.063) |
| 0 | -0.094*** | -0.163*** | -0.091*** | -0.176*** |
| | (0.006) | (0.028) | (0.011) | (0.049) |
| 1 | 0.003 | 0.001 | 0.026** | -0.034 |
| | (0.006) | (0.044) | (0.012) | (0.068) |
| 2 | 0.024*** | -0.093 | 0.013 | 0.145** |
| | (0.007) | (0.103) | (0.015) | (0.069) |
| 3 | 0.034*** | | -0.008 | |
| | (0.009) | | (0.021) | |
| *Fit statistics* | | | | |
| Observations | 14,246,619 | 37,991 | 3,268,160 | 113,665 |
| $R^2$ | 0.76653 | 0.75320 | 0.73887 | 0.76659 |
| Within $R^2$ | $9.24 \times 10^{-5}$ | 0.00318 | $8.87 \times 10^{-5}$ | 0.00049 |
| Mean outcome | 0.541 | 0.648 | 0.550 | 0.584 |

*Clustered (person-specific) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Note: Includes person-specific and year-quarter fixed effects.

**Table B.6:** Event study results for log of real monthly income (in pesos)

| | Log real monthly income (pesos) | | | |
|---|---|---|---|---|
| | Non migrant | International migrant | Non migrant with ties | Internal migrant |
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| -4 | 0.0419 | | -0.0761 | |
| | (0.1557) | | (0.3538) | |
| -3 | -0.2318** | -0.3187 | 0.0393 | 1.180 |
| | (0.1119) | (0.9864) | (0.2384) | (1.221) |
| -2 | 0.0083 | -0.1661 | -0.1433 | 0.6648 |
| | (0.0905) | (0.6274) | (0.1987) | (0.6095) |
| 0 | 0.2451*** | -0.1216 | 0.3343** | -0.9276 |
| | (0.0792) | (0.3910) | (0.1643) | (0.7619) |
| 1 | -0.1467 | -0.7137 | 0.2354 | -0.3969 |
| | (0.0898) | (0.6499) | (0.1849) | (0.9212) |
| 2 | 0.0551 | 1.570 | 0.2354 | -3.062 |
| | (0.1058) | (1.533) | (0.2307) | (1.972) |
| 3 | 0.2114 | | 0.2198 | |
| | (0.1387) | | (0.2918) | |
| *Fit statistics* | | | | |
| Observations | 5,536,561 | 19,341 | 1,246,053 | 50,987 |
| $R^2$ | 0.49855 | 0.70279 | 0.50603 | 0.69316 |
| Within $R^2$ | $6.46 \times 10^{-6}$ | 0.00030 | $7.81 \times 10^{-6}$ | 0.00025 |
| Mean outcome | 6.145 | 5.222 | 6.095 | 5.569 |

*Clustered (person-specific) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Note: Includes person-specific and year-quarter fixed effects.

**Table B.7:** Event study results for the probability of being in the informal sector

| | Informal sector job=1 | | | |
|---|---|---|---|---|
| | Non migrant | International migrant | Non migrant with ties | Internal migrant |
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| -4 | -0.003 | | 0.020 | |
| | (0.012) | | (0.031) | |
| -3 | -0.011 | -0.029 | -0.018 | -0.021 |
| | (0.009) | (0.084) | (0.021) | (0.049) |
| -2 | -0.009 | -0.034 | -0.021 | -0.053 |
| | (0.007) | (0.046) | (0.017) | (0.038) |
| 0 | 0.009 | 0.080** | 0.008 | 0.020 |
| | (0.007) | (0.033) | (0.014) | (0.059) |
| 1 | -0.002 | 0.086* | -0.018 | -0.071* |
| | (0.008) | (0.052) | (0.016) | (0.041) |
| 2 | -0.009 | 0.046 | 0.005 | -0.141 |
| | (0.009) | (0.121) | (0.019) | (0.148) |
| 3 | -0.005 | | -0.027 | |
| | (0.013) | | (0.027) | |
| *Fit statistics* | | | | |
| Observations | 5,536,561 | 19,341 | 1,246,053 | 50,987 |
| $R^2$ | 0.71852 | 0.76653 | 0.71968 | 0.77713 |
| Within $R^2$ | $3.32 \times 10^{-6}$ | 0.00096 | $1.1 \times 10^{-5}$ | 0.00013 |
| Mean outcome | 0.211 | 0.282 | 0.221 | 0.226 |

*Clustered (person-specific) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Note: Includes person-specific and year-quarter fixed effects.

## B.7 Heterogeneity: length of preparations to migrate

**Table B.8:** Odds ratio from the regression on preparations to migrate by length of preparations

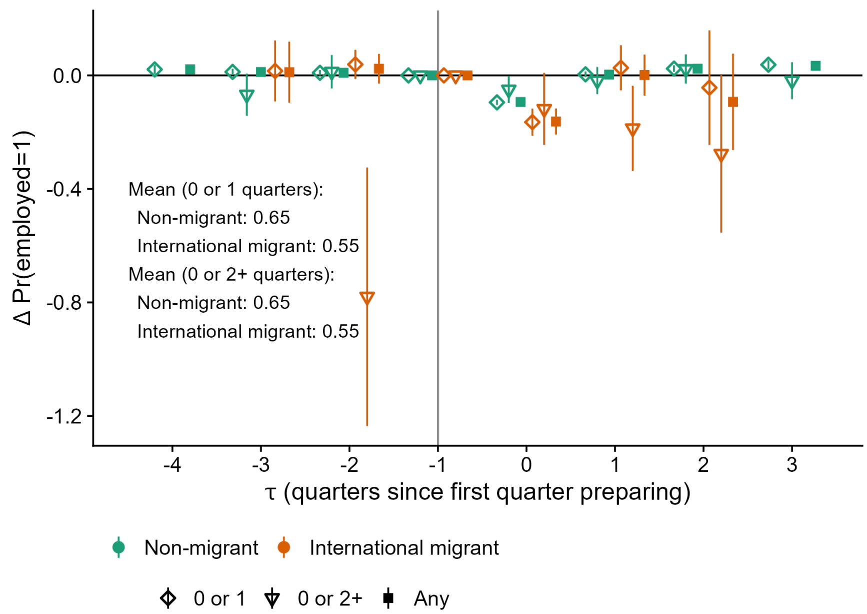
| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Ever preparing to migrate (0/1) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Intercept | 0.001*** | 0.001*** | 0.00000*** | 0.012*** | 0.012*** | 0.00000*** |
| | (0.001,0.002) | (0.001,0.002) | (0.00000,0.00004) | (0.002,0.073) | (0.002,0.077) | (0.000,0.024) |
| Female=1 | 0.438*** | 0.450*** | 0.151*** | 0.333*** | 0.346*** | 0.117** |
| | (0.416,0.461) | (0.428,0.474) | (0.104,0.218) | (0.244,0.455) | (0.252,0.473) | (0.015,0.935) |
| Age | 1.162*** | 1.157*** | 1.349*** | 1.093*** | 1.080*** | 1.735*** |
| | (1.151,1.173) | (1.146,1.168) | (1.268,1.434) | (1.045,1.144) | (1.032,1.131) | (1.234,2.440) |
| Age squared | 0.998*** | 0.998*** | 0.996*** | 0.999*** | 0.999*** | 0.992*** |
| | (0.998,0.998) | (0.998,0.998) | (0.995,0.997) | (0.998,0.999) | (0.998,0.999) | (0.987,0.997) |
| **Region in Mexico (ref: Historic migrant-sending states)** | | | | | | |
| North | 0.988 | 0.958 | 2.081*** | 1.497*** | 1.403** | 4.056*** |
| | (0.936,1.042) | (0.907,1.012) | (1.592,2.718) | (1.137,1.970) | (1.056,1.863) | (1.400,11.752) |
| Center | 0.854*** | 0.852*** | 0.920 | 0.791** | 0.784** | 0.880 |
| | (0.814,0.896) | (0.812,0.895) | (0.697,1.214) | (0.642,0.974) | (0.633,0.971) | (0.373,2.074) |
| Southeast | 0.617*** | 0.620*** | 0.565*** | 0.533*** | 0.542*** | 0.265 |
| | (0.576,0.660) | (0.578,0.664) | (0.392,0.814) | (0.372,0.763) | (0.375,0.783) | (0.049,1.424) |
| **Place of birth (ref: Mexico)** | | | | | | |
| U.S. | 7.421*** | 6.910*** | 18.551*** | 1.010 | 1.058 | 0.00000 |
| | (6.497,8.477) | (6.007,7.950) | (12.140,28.347) | (0.631,1.616) | (0.660,1.695) | (0.000,Inf.000) |
| Rest of the world | 1.436** | 1.466*** | 0.736 | 0.343* | 0.253* | 1.979 |
| | (1.082,1.907) | (1.101,1.952) | (0.103,5.261) | (0.106,1.110) | (0.061,1.043) | (0.133,29.469) |
| **Urban=1** | 0.668*** | 0.684*** | 0.363*** | 0.654*** | 0.687*** | 0.272*** |
| | (0.644,0.693) | (0.658,0.710) | (0.298,0.441) | (0.543,0.787) | (0.569,0.830) | (0.105,0.707) |
| **Current education (ref: High school)** | | | | | | |
| None | 0.721*** | 0.729*** | 0.545* | 0.554* | 0.531* | 0.895 |
| | (0.634,0.820) | (0.639,0.831) | (0.272,1.092) | (0.289,1.061) | (0.269,1.048) | (0.102,7.818) |
| Elementary | 0.824*** | 0.829*** | 0.703** | 0.824 | 0.848 | 0.523 |
| | (0.778,0.873) | (0.782,0.880) | (0.521,0.949) | (0.646,1.052) | (0.660,1.089) | (0.189,1.451) |
| Middle school | 0.923*** | 0.918*** | 1.066 | 0.975 | 0.972 | 1.039 |
| | (0.877,0.972) | (0.871,0.967) | (0.825,1.378) | (0.780,1.218) | (0.773,1.223) | (0.436,2.476) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Trade school | 0.927 | 0.927 | 0.955 | 1.099 | 1.178 | 0.00000 |
| | (0.845,1.018) | (0.843,1.019) | (0.573,1.590) | (0.650,1.857) | (0.696,1.993) | (0.000,Inf.000) |
| College | 1.076** | 1.081*** | 0.903 | 0.766 | 0.798 | 0.232 |
| | (1.017,1.137) | (1.022,1.144) | (0.665,1.227) | (0.548,1.071) | (0.568,1.121) | (0.027,1.964) |
| Graduate studies | 1.217*** | 1.195** | 1.820* | 3.420*** | 2.807** | 18.187*** |
| | (1.057,1.400) | (1.034,1.380) | (0.967,3.424) | (1.628,7.185) | (1.232,6.397) | (2.631,125.737) |
| **Labor force status (ref: Employed)** | | | | | | |
| Unemployed | 3.730*** | 3.773*** | 2.841*** | 5.626*** | 5.621*** | 4.631*** |
| | (3.525,3.947) | (3.562,3.996) | (2.096,3.851) | (4.560,6.941) | (4.538,6.961) | (1.834,11.696) |
| Available | 0.757*** | 0.766*** | 0.539* | 0.502** | 0.517** | 0.00000 |
| | (0.682,0.841) | (0.689,0.852) | (0.261,1.112) | (0.284,0.891) | (0.292,0.917) | (0.000,Inf.000) |
| Unavailable | 0.398*** | 0.400*** | 0.384*** | 0.778* | 0.730** | 2.135 |
| | (0.369,0.429) | (0.371,0.432) | (0.245,0.602) | (0.580,1.044) | (0.539,0.990) | (0.705,6.469) |
| **Has partner=1** | 0.909*** | 0.907*** | 0.893 | 1.121 | 1.123 | 0.881 |
| | (0.860,0.960) | (0.858,0.959) | (0.673,1.187) | (0.849,1.480) | (0.845,1.492) | (0.258,3.006) |
| **Relationship to household head (ref: head of household)** | | | | | | |
| Spouse/Partner | 0.577*** | 0.585*** | 0.454*** | 0.858 | 0.925 | 0.00000 |
| | (0.535,0.621) | (0.543,0.631) | (0.283,0.728) | (0.631,1.167) | (0.679,1.261) | (0.000,Inf.000) |
| Child | 0.723*** | 0.738*** | 0.417*** | 0.649*** | 0.667*** | 0.418 |
| | (0.679,0.769) | (0.693,0.786) | (0.297,0.585) | (0.483,0.871) | (0.493,0.903) | (0.121,1.451) |
| Grandchild | 0.539*** | 0.551*** | 0.317** | 0.669 | 0.664 | 0.889 |
| | (0.453,0.640) | (0.463,0.656) | (0.111,0.910) | (0.360,1.241) | (0.351,1.255) | (0.073,10.867) |
| Daughter/Son in-law | 0.661*** | 0.660*** | 0.713 | 0.559** | 0.573** | 0.477 |
| | (0.579,0.755) | (0.576,0.757) | (0.395,1.287) | (0.344,0.910) | (0.348,0.943) | (0.060,3.775) |
| Other | 0.583*** | 0.596*** | 0.281*** | 0.582** | 0.600** | 0.233 |
| | (0.521,0.652) | (0.532,0.668) | (0.129,0.611) | (0.369,0.917) | (0.378,0.954) | (0.024,2.316) |
| **Share of household members** | | | | | | |
| Children | 0.737*** | 0.739*** | 0.713 | 0.827 | 0.789 | 2.075 |
| | (0.669,0.812) | (0.670,0.816) | (0.436,1.165) | (0.537,1.275) | (0.506,1.232) | (0.363,11.877) |
| Elderly (> 65) | 0.817 | 0.813 | 0.788 | 0.566 | 0.553 | 0.506 |
| | (0.627,1.064) | (0.621,1.064) | (0.177,3.503) | (0.146,2.194) | (0.139,2.198) | (0.001,338.033) |
| **Income quartile (ref: lowest 2 quartile/ 0 income)** | | | | | | |
| Income Q3 | 1.428*** | 1.440*** | 1.151 | 1.120 | 1.114 | 1.169 |
| | (1.355,1.504) | (1.366,1.519) | (0.883,1.502) | (0.920,1.363) | (0.912,1.362) | (0.497,2.750) |
| Income Q4 | 0.789*** | 0.809*** | 0.443*** | 0.825 | 0.802* | 1.073 |
| | (0.744,0.838) | (0.761,0.859) | (0.329,0.597) | (0.653,1.042) | (0.631,1.021) | (0.419,2.748) |
| **Remittances** | | | | | | |
| Household receives remittances=1 | 1.512*** | 1.498*** | 1.977*** | 1.316*** | 1.351*** | 0.828 |
| | (1.434,1.594) | (1.420,1.581) | (1.523,2.566) | (1.114,1.554) | (1.139,1.602) | (0.402,1.706) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Real remittances received (state) | 1.096*** | 1.096*** | 1.111* | 0.943 | 0.948 | 0.898 |
| | (1.068,1.124) | (1.068,1.125) | (0.981,1.259) | (0.835,1.064) | (0.837,1.073) | (0.541,1.493) |
| **Macroeconomic trends** | | | | | | |
| US-Mex wage difference | 0.756* | 0.768* | 0.484 | 0.836 | 0.768 | 1.562 |
| | (0.563,1.016) | (0.568,1.037) | (0.104,2.257) | (0.207,3.381) | (0.184,3.200) | (0.001,1,732.527) |
| Unemployment rate (US) | 0.953 | 0.949 | 1.073 | 0.983 | 1.116 | 0.102* |
| | (0.848,1.071) | (0.843,1.069) | (0.597,1.931) | (0.564,1.712) | (0.630,1.977) | (0.009,1.144) |
| Employment rate (Mex) | 0.922*** | 0.925*** | 0.844** | 0.914 | 0.940 | 0.565** |
| | (0.897,0.947) | (0.899,0.951) | (0.733,0.972) | (0.805,1.038) | (0.825,1.071) | (0.336,0.948) |
| Distance to border | 0.952*** | 0.946*** | 1.104 | 1.243*** | 1.220** | 1.716 |
| | (0.925,0.981) | (0.918,0.975) | (0.963,1.265) | (1.061,1.456) | (1.037,1.436) | (0.898,3.279) |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,242,182 | 3,241,714 | 3,230,124 | 17,338 | 17,299 | 16,672 |
| Log Likelihood | -74,533.320 | -72,414.960 | -3,957.896 | -2,610.180 | -2,506.666 | -212.719 |
| Akaike Inf. Crit. | 149,168.600 | 144,931.900 | 8,017.791 | 5,322.359 | 5,115.332 | 527.438 |

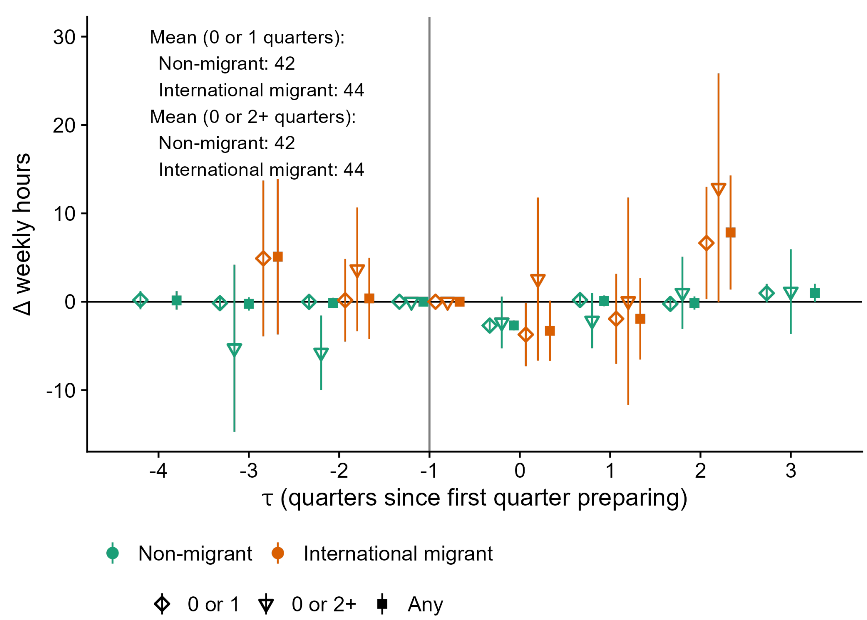
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

**Figure B.5:** Changes in probability of being employed relative to event, by duration of preparations



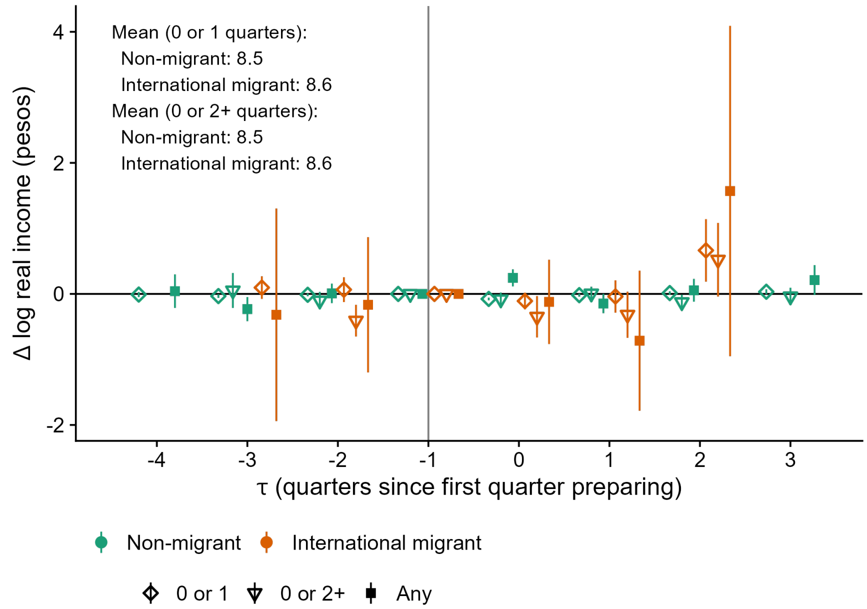

Note: Error bars represent 95% confidence intervals.

**Figure B.6:** Changes in weekly hours worked relative to event, by duration of preparations



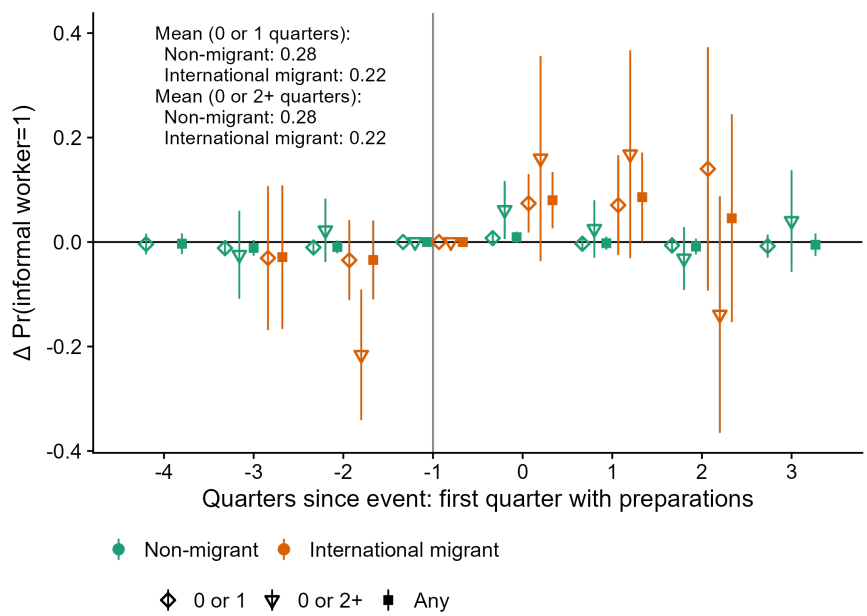

Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

**Figure B.7:** Changes in log real income relative to event, by duration of preparations




Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

**Figure B.8:** Changes in probability of working in the informal sector relative to event, by duration of preparations




Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

## B.8 Heterogeneity: reasons for migration

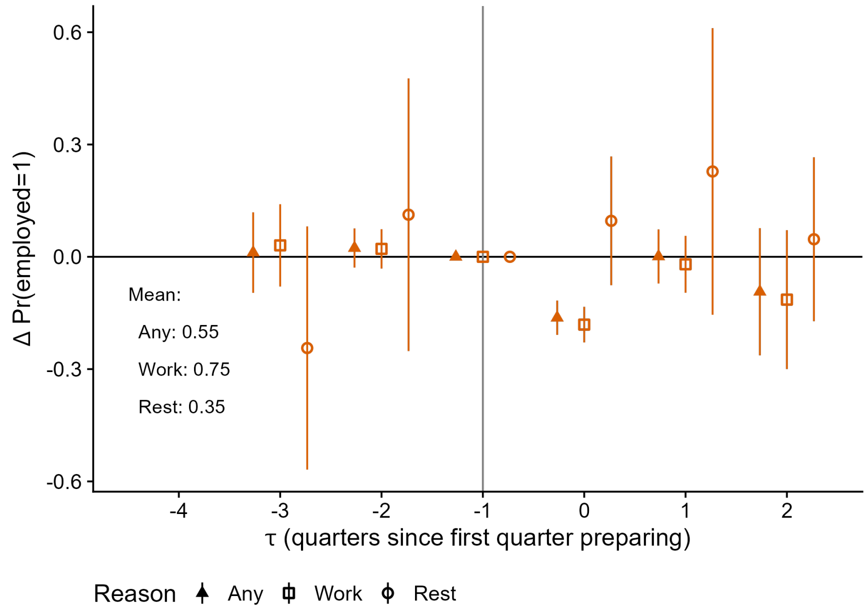
**Table B.9:** Odds ratio from the regression on preparations to migrate, by reasons of migration for international migrants

| | Ever preparing to migrate (0/1) *International migrant* | | | |
|---|---|---|---|---|
| Sample | Full Sample | Full Sample | Only work | Education, Union/Divorce Family, Health Safety |
| Intercept | 0.012*** | 0.015*** | 0.019*** | 0.0002** |
| | (0.002,0.072) | (0.002,0.094) | (0.003,0.134) | (0.00000,0.389) |
| Female=1 | 0.335*** | 0.437*** | 0.403*** | 0.637 |
| | (0.245,0.457) | (0.315,0.607) | (0.275,0.590) | (0.313,1.297) |
| Age | 1.093*** | 1.080*** | 1.070*** | 1.129 |
| | (1.044,1.143) | (1.030,1.133) | (1.018,1.124) | (0.933,1.367) |
| Age squared | 0.999*** | 0.999*** | 0.999*** | 0.998 |
| | (0.998,0.999) | (0.998,0.999) | (0.998,1.000) | (0.995,1.001) |
| **Region in Mexico (ref: Historic migrant-sending states)** | | | | |
| North | 1.490*** | 1.615*** | 1.572*** | 2.165* |
| | (1.132,1.960) | (1.220,2.137) | (1.169,2.115) | (0.880,5.325) |
| Center | 0.788** | 0.765** | 0.788** | 0.361 |
| | (0.640,0.970) | (0.620,0.943) | (0.636,0.975) | (0.098,1.324) |
| Southeast | 0.526*** | 0.509*** | 0.542*** | 0.100** |
| | (0.367,0.754) | (0.354,0.733) | (0.374,0.786) | (0.011,0.951) |
| **Place of birth (ref: Mexico)** | | | | |
| Outside Mexico | 0.815 | 0.955 | 1.109 | 0.624 |
| | (0.526,1.262) | (0.602,1.513) | (0.667,1.844) | (0.202,1.927) |
| **Urban=1** | 0.653*** | 0.690*** | 0.684*** | 1.023 |
| | (0.542,0.786) | (0.572,0.834) | (0.563,0.832) | (0.478,2.193) |
| **Current education (ref: High school)** | | | | |
| None/Elementary | 0.807* | 0.800* | 0.761** | 1.876 |
| | (0.633,1.028) | (0.626,1.021) | (0.593,0.976) | (0.502,7.005) |
| Middle school | 0.973 | 0.949 | 0.917 | 1.378 |
| | (0.779,1.216) | (0.758,1.188) | (0.729,1.153) | (0.416,4.563) |
| Trade school | 1.084 | 1.088 | 0.982 | 4.161 |
| | (0.642,1.831) | (0.642,1.844) | (0.563,1.714) | (0.716,24.178) |
| College | 0.754* | 0.750 | 0.655** | 2.065 |
| | (0.540,1.053) | (0.531,1.058) | (0.449,0.956) | (0.673,6.343) |
| Graduate studies | 3.277*** | 3.784*** | 2.218 | 11.656*** |
| | (1.560,6.884) | (1.767,8.101) | (0.746,6.598) | (2.765,49.141) |
| **Labor force status (ref: Employed)** | | | | |
| Unemployed | 5.612*** | 5.536*** | 5.771*** | 2.928* |
| | (4.549,6.923) | (4.478,6.843) | (4.645,7.171) | (0.968,8.857) |
| Available | 0.505** | 0.529** | 0.477** | 0.963 |
| | (0.285,0.894) | (0.298,0.938) | (0.250,0.910) | (0.241,3.850) |
| Unavailable | 0.779* | 0.876 | 0.951 | 0.577 |
| | (0.581,1.046) | (0.651,1.179) | (0.698,1.296) | (0.216,1.539) |
| **Has partner=1** | 1.119 | 1.142 | 1.158 | 0.973 |
| | (0.848,1.477) | (0.860,1.515) | (0.863,1.554) | (0.335,2.828) |

| | | | | |
|---|---|---|---|---|
| **Relationship to household head (ref: head of household)** | | | | |
| Spouse/Partner | 0.852 | 0.815 | 0.827 | 0.336 |
| | (0.627,1.159) | (0.595,1.117) | (0.600,1.140) | (0.062,1.833) |
| Child | 0.650*** | 0.666*** | 0.679** | 0.359 |
| | (0.484,0.873) | (0.493,0.898) | (0.498,0.926) | (0.099,1.294) |
| Grandchild | 0.666 | 0.779 | 0.771 | 0.651 |
| | (0.359,1.236) | (0.416,1.457) | (0.389,1.525) | (0.096,4.418) |
| Daughter/Son in-law | 0.554** | 0.589** | 0.605** | 0.307 |
| | (0.341,0.901) | (0.361,0.959) | (0.366,0.999) | (0.030,3.098) |
| Other | 0.565** | 0.573** | 0.615* | 0.293 |
| | (0.359,0.890) | (0.356,0.922) | (0.373,1.014) | (0.059,1.462) |
| **Share of household members** | | | | |
| Children | 0.833 | 0.867 | 0.902 | 0.604 |
| | (0.541,1.284) | (0.561,1.342) | (0.577,1.409) | (0.057,6.381) |
| Elderly ($>65$) | 0.585 | 0.520 | 0.454 | 1.792 |
| | (0.151,2.264) | (0.127,2.123) | (0.101,2.044) | (0.024,132.671) |
| **Income quartile (ref: lowest 2 quartile/ 0 income)** | | | | |
| Income Q3 | 1.117 | 1.096 | 1.062 | 2.085 |
| | (0.918,1.360) | (0.900,1.336) | (0.868,1.301) | (0.854,5.088) |
| Income Q4 | 0.824 | 0.812* | 0.819 | 0.608 |
| | (0.653,1.041) | (0.642,1.028) | (0.643,1.041) | (0.186,1.983) |
| **Remittances** | | | | |
| Household receives remittances=1 | 1.319*** | 1.323*** | 1.346*** | 0.853 |
| | (1.116,1.558) | (1.117,1.566) | (1.132,1.600) | (0.362,2.012) |
| Real remittances received (state) | 0.942 | 0.936 | 0.924 | 0.894 |
| | (0.835,1.063) | (0.828,1.059) | (0.812,1.051) | (0.532,1.504) |
| **Macroeconomic trends** | | | | |
| US-Mex wage difference | 0.809 | 0.814 | 0.879 | 0.146 |
| | (0.200,3.272) | (0.196,3.377) | (0.199,3.874) | (0.0004,50.883) |
| Unemployment rate (US) | 0.985 | 0.953 | 0.950 | 1.645 |
| | (0.565,1.715) | (0.544,1.672) | (0.530,1.701) | (0.130,20.739) |
| Employment rate (Mex) | 0.915 | 0.909 | 0.909 | 0.866 |
| | (0.806,1.039) | (0.800,1.034) | (0.796,1.038) | (0.486,1.541) |
| Distance to border | 1.229** | 1.256*** | 1.243** | 1.467 |
| | (1.049,1.439) | (1.068,1.476) | (1.048,1.474) | (0.872,2.468) |
| Education | | 0.507** | | |
| | | (0.297,0.864) | | |
| Union/Divorce | | 0.303*** | | |
| | | (0.141,0.652) | | |
| Family reunification | | 0.336*** | | |
| | | (0.183,0.618) | | |
| Health or Safety | | 0.493 | | |
| | | (0.065,3.722) | | |
| Year | Yes | Yes | Yes | Yes |
| Quarter | Yes | Yes | Yes | Yes |
| Observations | 17,338 | 16,414 | 12,738 | 3,676 |
| Log Likelihood | -2,612.814 | -2,538.398 | -2,344.709 | -171.130 |
| Akaike Inf. Crit. | 5,323.628 | 5,182.797 | 4,787.417 | 440.260 |

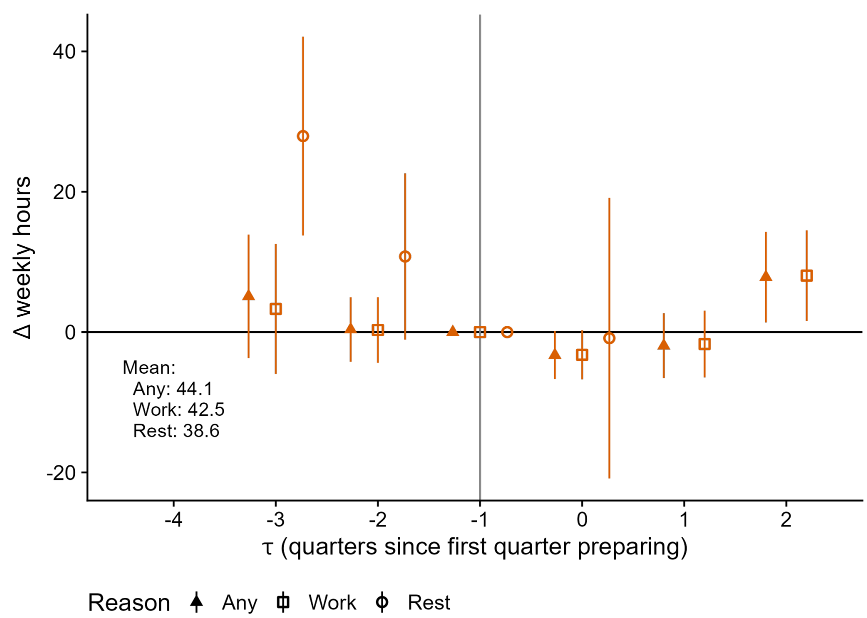
Note: $^{*}p < 0.1$;$^{**}p < 0.05$;$^{***}p < 0.01$

**Figure B.9:** Changes in probability of being employed relative to event, by reason of migration for international migrants



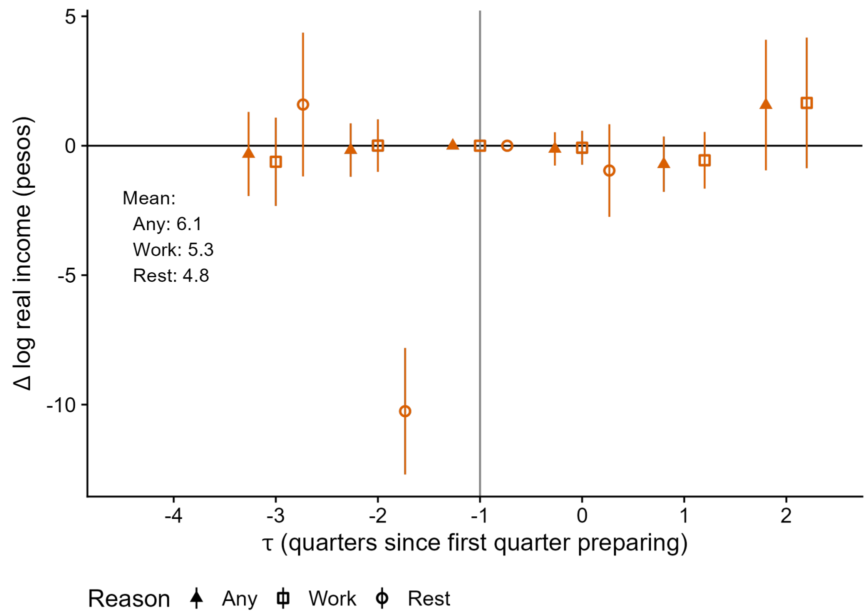

Note: Error bars represent 95% confidence intervals.

**Figure B.10:** Changes in weekly hours worked relative to event, by reason of migration for international migrants



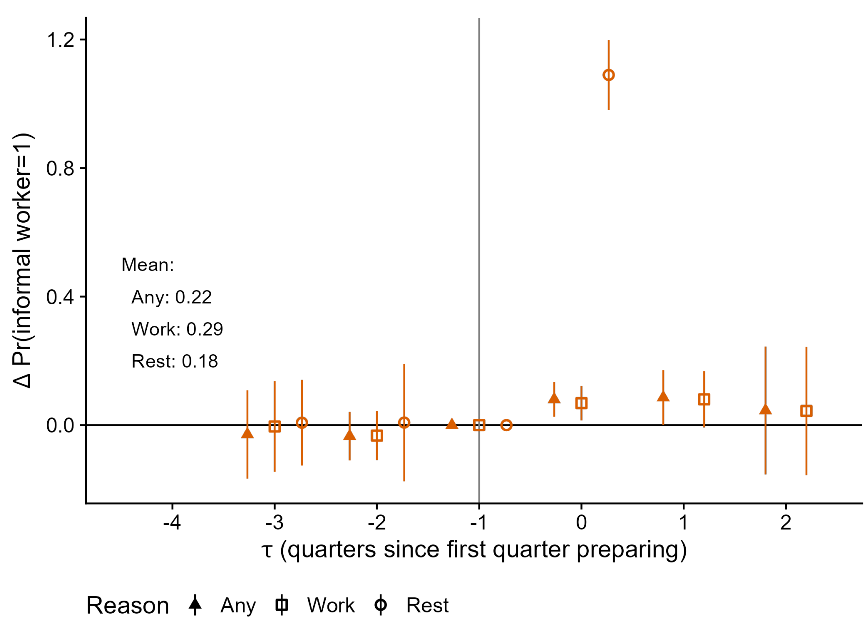

Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

**Figure B.11:** Changes in log real income relative to event, by reason of migration for international migrants




Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

**Figure B.12:** Changes in probability of working in the informal sector relative to event, by reason of migration for international migrants




Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

## B.9 Heterogeneity: other categories of migrants

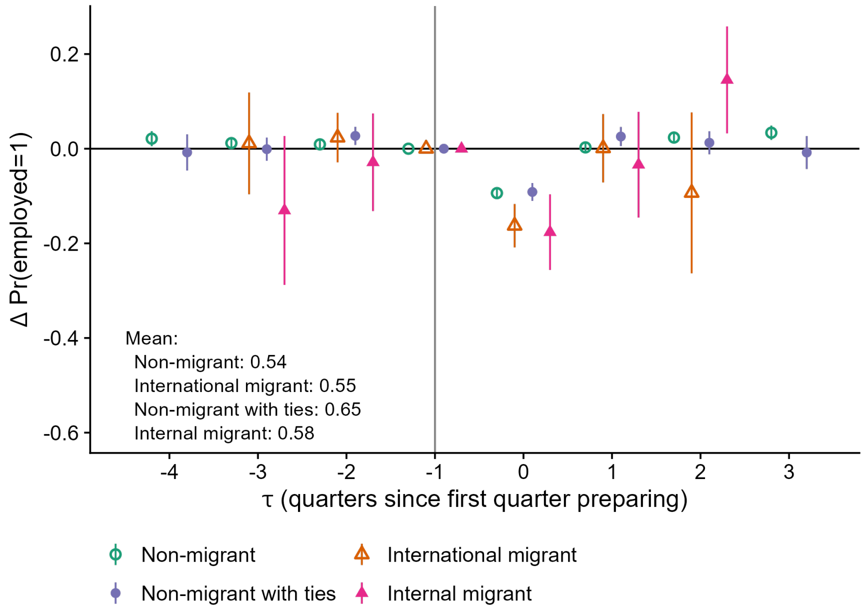
**Table B.10:** Odds ratio from the regression on preparations to migrate with a comparison to non-migrants with migrant ties and internal migrants

| | Ever preparing to migrate (0/1) | | | |
|---|---|---|---|---|
| | Non migrants | International migrants | Non migrants with ties | Internal migrants |
| | (1) | (2) | (3) | (4) |
| Intercept | 0.001*** | 0.012*** | 0.001*** | 0.005*** |
| | (0.001,0.002) | (0.002,0.073) | (0.0003,0.002) | (0.0004,0.060) |
| Female==1 | 0.438*** | 0.333*** | 0.446*** | 0.430*** |
| | (0.416,0.461) | (0.244,0.455) | (0.404,0.493) | (0.313,0.591) |
| Age | 1.162*** | 1.093*** | 1.149*** | 1.118*** |
| | (1.151,1.173) | (1.045,1.144) | (1.126,1.172) | (1.048,1.193) |
| Age squared | 0.998*** | 0.999*** | 0.998*** | 0.998*** |
| | (0.998,0.998) | (0.998,0.999) | (0.998,0.998) | (0.998,0.999) |
| **Region in Mexico (ref: Historic migrant-sending states)** | | | | |
| North | 0.988 | 1.497*** | 0.999 | 1.009 |
| | (0.936,1.042) | (1.137,1.970) | (0.887,1.125) | (0.705,1.444) |
| Center | 0.854*** | 0.791** | 0.926 | 0.843 |
| | (0.814,0.896) | (0.642,0.974) | (0.830,1.032) | (0.623,1.140) |
| Southeast | 0.617*** | 0.533*** | 0.576*** | 0.598** |
| | (0.576,0.660) | (0.372,0.763) | (0.493,0.673) | (0.398,0.899) |
| **Place of birth (ref: Mexico)** | | | | |
| Rest of the World | 1.436** | 0.343* | 2.297*** | |
| | (1.082,1.907) | (0.106,1.110) | (1.221,4.323) | |
| U.S. | 7.421*** | 1.010 | 7.668*** | |
| | (6.497,8.477) | (0.631,1.616) | (5.582,10.534) | |
| Outside Mexico | | | | 3.852*** |
| | | | | (1.554,9.549) |
| **Urban=1** | 0.668*** | 0.654*** | 0.702*** | 0.825 |
| | (0.644,0.693) | (0.543,0.787) | (0.646,0.763) | (0.644,1.057) |
| **Current education (ref: High school)** | | | | |
| None | 0.721*** | 0.554* | 0.600*** | 1.201 |
| | (0.634,0.820) | (0.289,1.061) | (0.456,0.789) | (0.534,2.704) |
| Elementary | 0.824*** | 0.824 | 0.739*** | 1.025 |
| | (0.778,0.873) | (0.646,1.052) | (0.649,0.840) | (0.697,1.507) |
| Middle school | 0.923*** | 0.975 | 0.898* | 1.127 |
| | (0.877,0.972) | (0.780,1.218) | (0.800,1.008) | (0.806,1.576) |
| Trade school | 0.927 | 1.099 | 1.014 | 0.868 |
| | (0.845,1.018) | (0.650,1.857) | (0.824,1.248) | (0.392,1.924) |
| College | 1.076** | 0.766 | 1.027 | 1.084 |
| | (1.017,1.137) | (0.548,1.071) | (0.897,1.175) | (0.756,1.554) |
| Graduate studies | 1.217*** | 3.420*** | 1.558** | 3.166*** |
| | (1.057,1.400) | (1.628,7.185) | (1.103,2.202) | (1.610,6.226) |
| **Relationship to household head (ref: head of household)** | | | | |
| Spouse/Partner | 0.577*** | 0.858 | 0.637*** | 0.371** |
| | (0.535,0.621) | (0.631,1.167) | (0.542,0.749) | (0.168,0.816) |
| Child | 0.723*** | 0.649*** | 0.798*** | 0.791 |

| | | | | |
|---|---|---|---|---|
| | (0.679,0.769) | (0.483,0.871) | (0.700,0.911) | (0.535,1.170) |
| Other | 0.583*** | 0.582** | 0.647*** | 0.651* |
| | (0.521,0.652) | (0.369,0.917) | (0.526,0.797) | (0.423,1.003) |
| Grandchild | 0.539*** | 0.669 | 0.712** | 0.593 |
| | (0.453,0.640) | (0.360,1.241) | (0.529,0.959) | (0.259,1.355) |
| Daughter/Son in-law | 0.661*** | 0.559** | 0.546*** | 0.702 |
| | (0.579,0.755) | (0.344,0.910) | (0.410,0.728) | (0.390,1.265) |
| **Has partner** | 0.909*** | 1.121 | 1.023 | 1.283 |
| | (0.860,0.960) | (0.849,1.480) | (0.912,1.148) | (0.922,1.785) |
| **Share of household members** | | | | |
| % Children | 0.737*** | 0.827 | 0.783** | 0.808 |
| | (0.669,0.812) | (0.537,1.275) | (0.615,0.998) | (0.390,1.673) |
| % Elderly | 0.817 | 0.566 | 1.016 | 1.004 |
| | (0.627,1.064) | (0.146,2.194) | (0.506,2.039) | (0.202,4.993) |
| **Labor force status (ref: Employed)** | | | | |
| Unemployed | 3.730*** | 5.626*** | 3.739*** | 4.099*** |
| | (3.525,3.947) | (4.560,6.941) | (3.310,4.224) | (3.047,5.512) |
| Available | 0.757*** | 0.502** | 0.647*** | 0.438* |
| | (0.682,0.841) | (0.284,0.891) | (0.516,0.812) | (0.190,1.011) |
| Unavailable | 0.398*** | 0.778* | 0.431*** | 0.484*** |
| | (0.369,0.429) | (0.580,1.044) | (0.369,0.504) | (0.301,0.780) |
| **Remittances** | | | | |
| Household receives remittances=1 | 1.512*** | 1.316*** | 1.241*** | 1.070 |
| | (1.434,1.594) | (1.114,1.554) | (1.122,1.372) | (0.816,1.404) |
| Real remittances received (state) | 1.096*** | 0.943 | 1.081*** | 1.041 |
| | (1.068,1.124) | (0.835,1.064) | (1.021,1.145) | (0.882,1.229) |
| **Macroeconomic trends** | | | | |
| US-Mex wage difference | 0.756* | 0.836 | 0.462** | 1.999 |
| | (0.563,1.016) | (0.207,3.381) | (0.235,0.909) | (0.286,13.967) |
| Distance to border | 0.952*** | 1.243*** | 0.949 | 0.958 |
| | (0.925,0.981) | (1.061,1.456) | (0.889,1.013) | (0.801,1.147) |
| Unemployment rate (US) | 0.953 | 0.983 | 0.860 | 0.688 |
| | (0.848,1.071) | (0.564,1.712) | (0.659,1.122) | (0.326,1.451) |
| Employment rate (Mex) | 0.922*** | 0.914 | 0.875*** | 0.927 |
| | (0.897,0.947) | (0.805,1.038) | (0.823,0.930) | (0.785,1.094) |
| **Income quartile (ref: lowest 2 quartile/ 0 income)** | | | | |
| Income Q3 | 1.428*** | 1.120 | 1.384*** | 1.413** |
| | (1.355,1.504) | (0.920,1.363) | (1.233,1.553) | (1.056,1.891) |
| Income Q4 | 0.789*** | 0.825 | 0.884* | 0.767 |
| | (0.744,0.838) | (0.653,1.042) | (0.770,1.014) | (0.539,1.091) |
| Year | Yes | Yes | Yes | Yes |
| Quarter | Yes | Yes | Yes | Yes |
| Observations | 3,242,182 | 17,338 | 584,159 | 52,509 |
| Log Likelihood | -74,533.320 | -2,610.180 | -14,572.940 | -1,681.290 |
| Akaike Inf. Crit. | 149,168.600 | 5,322.359 | 29,247.880 | 3,462.579 |

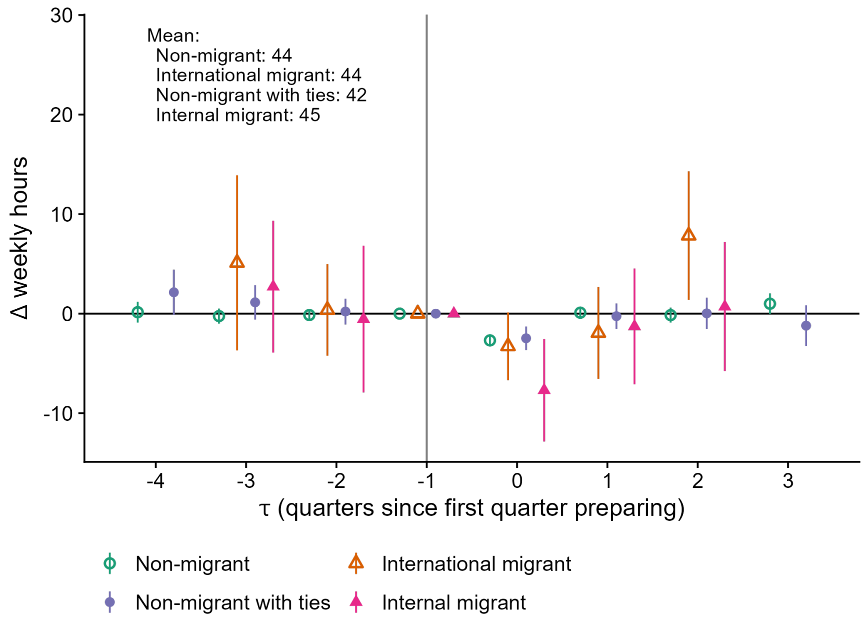
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

**Figure B.13:** Changes in probability of being employed relative to event, by categories of migration



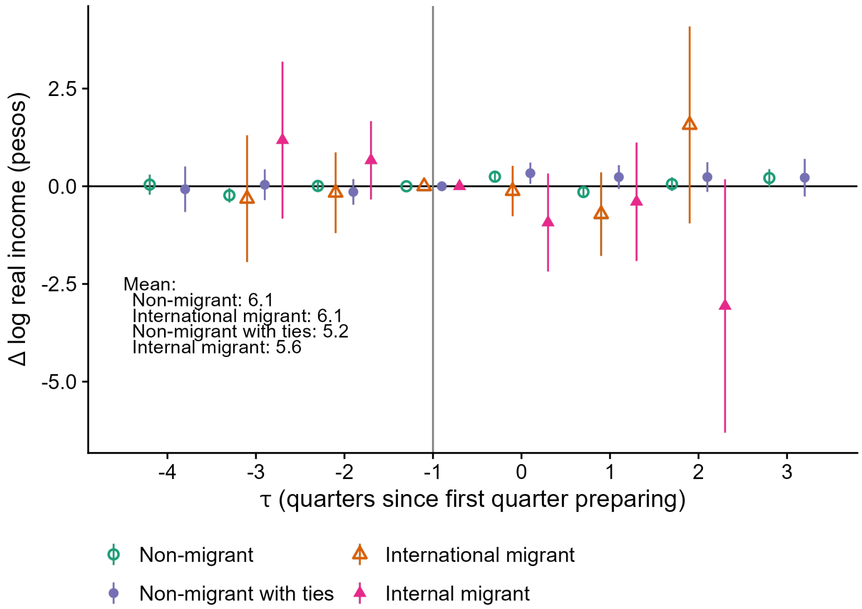

Note: Error bars represent 95% confidence intervals.

**Figure B.14:** Changes in weekly hours worked relative to event, by categories of migration



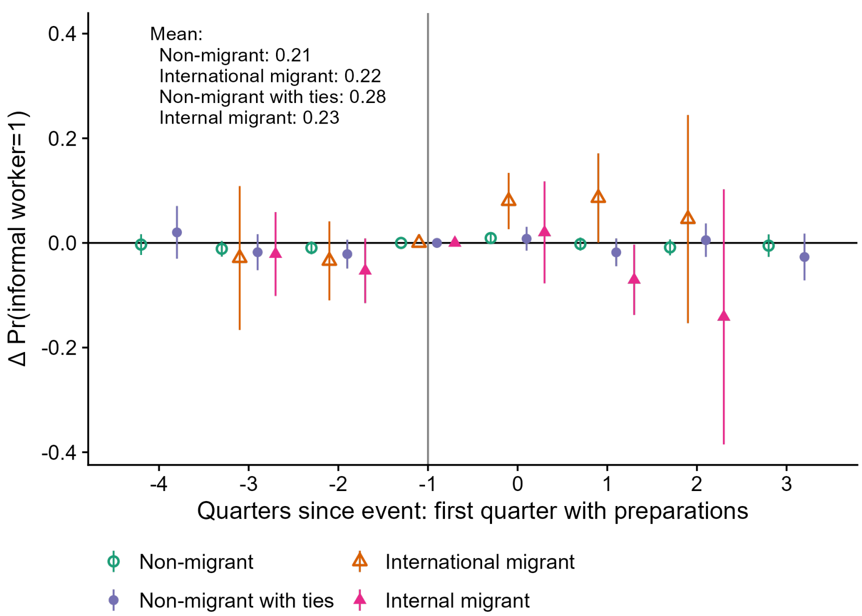

Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

**Figure B.15:** Changes in log real income relative to event, by categories of migration




Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

**Figure B.16:** Changes in probability of working in the informal sector relative to event, bby categories of migration




Note: Error bars represent 95% confidence intervals. Estimations are restricted to observations that have continuously been employed.

# Appendix C

# Appendix for Chapter 3

## C.1 Theory behind variable choice

### C.1.1 Aggregate covariates

The Neoclassical Economic Theory of migration would suggest that people observe their income, an expected income abroad and the costs of migration. Analyzing the present and future costs and incomes, people migrate when the expected return of migration is larger than the costs. To measure the expected difference in wages, I use the difference in the average wages in the manufacturing industry in Mexico and the US. This difference varies by quarter, but is fixed across all geographies. I expect that the smaller the wage differential, the lower the probability of being a migrant.

Borrowing from the gravity model, I calculate the minimum distance between each municipality centroid and the points of entry along the US-Mexico border using the driving distance from the Open Street Maps API. I expect that the closer to the border, the higher the probability of being a migrant.

In an attempt to control for the macroeconomic conditions in Mexico and the U.S., I include the quarterly average of monthly unemployment rate in the US and the employment rate in Mexico. If migrants decide to go where there are better job opportunities, then low unemployment rates in the US are attractive while low employment rates in Mexico are repulsive. Therefore, I expect a negative relationship between each of these rates and being a migrant.

As a proxy for migrant networks, I use the amount of remittances that a state in Mexico receives. States that have historically been important migrant origins have also received more remittances than other places in Mexico. Large remittances may be an indicator of strong ties of migrants to Mexico which is also suggestive of people in Mexico having access to migrant knowledge or connections. Altogether, I would expect that states that make a large migrant network (strong ties between origin and destination) receive large amounts of remittances and that this is a signal of people being exposed to migration. Therefore, I expect a positive relationship between remittances received by a state and the probability of being a migrant.

Since the environmental conditions can affect livelihoods of rural workers, I include a drought severity index for each municipality (which varies between quarters). While this variable doesn't capture sustained climatic events, or even the long-term change in conditions, it is indicative of contemporaneous conditions. Since Mexican migration has mostly come from rural and agricultural areas, I expect droughts in rural areas to increase the probability of migrating. Moreover, as droughts increase in severity, I expect the probability of being a migrant to also increase.

### C.1.2 Household covariates

The New Economics of Labor Migration (NELM) theory stresses that households make a joint decision of who should migrate. Therefore, I include variables on the composition of households.

First, I include the share of children and elderly members to understand the household dependency ratios. Higher ratios should mean that available income is divided among more people, such that there are incentives for people to migrate to increase available income. Theoretically, there shouldn't be a difference between whether a household is composed of children or the elderly.

Next, the regressions also include the kinship relationship to the household head. The household determines the number and the person that should migrate, and this may be a function of the household dynamics. For instance, if the objective of the household is to diversify income sources, then the household head will be the least likely to migrate. I expect that more central members of the family member such as the household head or the spouse are less likely to migrate, if the objective is to diversify income. However, if the household objective is to increase income then the household head is the most likely to migrate. If the household objective is family migration, then we will see broader family members to be more likely to migrate. In practice, I expect that there are many intersecting motives to migrate.

Lastly, I include a binary variable on the whether the household receives remittances from abroad or from another state. The logic behind this variable is similar to the state level remittance however, here I can measure the direct effect of having a migrant tie. Receiving remittance shows a direct connection to a migrant, which can lower the costs of migration and increase the probability of being a migrant.

## C.2 Variables

**Table C.1:** Description of variables

| Variable | Description | Categories | Reference group in regressions |
|---|---|---|---|
| Sex | Sex are reported to interviewers; not inferred by interviewers. Not gender. | Male, Female | Female |
| Age groups | Age binned into 10-year age groups from 10 to 100. First age group, 0-10, not included because outside of analytical sample | [10,20)-[90,100] | [20,30) |
| Education | Current level of education of respondents. Does not necessarily indicate completed education or years in school | No education, elementary (includes pre-school), middle school, high school, technical career, college and graduate studies. | High school |
| Regions in Mexico | States divided into regions based on Durand (2017, p.28): the Historic migrant-sending states (Aguascalientes, Colima, Durango, Guanajuato, Jalisco, Michoacán, Nayarit, San Luis Potosí, Zacatecas); states along the North (Baja California, Baja California Sur, Sinaloa, Sonora, Chihuahua, Coahuila, Nuevo León, Tamaulipas) border, states in the Center (Mexico City, Hidalgo, Querétaro, State of México, Morelos, Puebla, Tlaxcala, Guerrero) of Mexico and states in the Southeast (Chiapas, Tabasco, Quintana Roo, Campeche, Yucatán, Veracruz, Oaxaca) of Mexico. | Historic-migrant sending, North, Center, Southeast | Historic |
| Year | Year of interview, binned by 3 years | [2006,2008), (2008,2011], (2011,2014], (2014,2017], (2017,2019] | [2006,2008) |
| Urbanicity | Location is categorized as urban or rural by INEGI, based on population size of locality: less than 2,500 people is considered rural. | Urban, rural | Rural |
| Place of birth | Place of birth of respondents where rest of the world contains many nationalities, but fewer counts than the rest of foreign nationalities. I do not assume that place of birth is a proxy for country of citizenship. | Mexico, Guatemala, Spain, USA, rest of the world | Mexico |

*Continued on next page*

**Table C.1:** Description of variables

| Variable | Description | Categories | Reference group in regressions |
|---|---|---|---|
| Education | Current education level of respondents and does not represent 1) completed education or 2) completed level. I include levels of education instead of years because of the non-linearities of increasing education. Elementary school contains preschool. Graduate studies encompasses Master's and PhD degrees. Trade school includes teacher degree and a technical careers. | None, elementary school, middle school, high school, trade school, college and graduate studies | High school |
| Kinship | The ENOE records kinship relative to the household head. There are numerous categories but I synthesize them to 6. | Household head (HH), spouse of partner of HH, child of HH, grandchild of HH, daughter in-law or son in-law and remaining categories | HH |
| Partnership | A value of 1 indicates that a person is married or is living with their partner. A value of 0 indicates that a person is separated or divorced or widowed or single | Has partner, no partner | No partner |
| Share children (%) | Share of household members in a given quarter who are under the age of 18 | | |
| Share elderly (%) | Share of household members in a given quarter who are over the age of 75 | | |
| Labor force status | I use categories of the labor force status as defined by Instituto Nacional de Estadística y Geografía (2007, p.14-17). The labor force refers to the group of people that are willing and able to work, who are either employed (*"Población ocupada"*) or unemployed (*"Población desocupada"*). Those who are unemployed are actively seeking for a job. The population outside of the labor force are those who do not offer labor but instead depend on monetary or non monetary transfers. Some examples include students, and people who are retired. People who are available and out of the labor force are interested in working but not actively looking for a job (or working). Those who are unavailable and out of the labor force are not working, are not interested in work or who cannot work. Not applicable refers to people aged 14 and less who are not legally allowed to work. | Not applicable, unemployed, employed, available, unavailable | Employed |

*Continued on next page*

**Table C.1:** Description of variables

| Variable | Description | Categories | Reference group in regressions |
|---|---|---|---|
| Household receives remittances | Takes value of one if any member in the household receives any remittances (from abroad, from another state, or from within a state) in a quarter. | Any household member receives/ doesn't receive | No member of household receives remittances |
| Remittances received by states | Remittances in real dollars that were received by the state of residence of the respondent in a given quarter. I use demeaned and standardized values. Source: Banxico (Remittances per state, Balance of Payments) | | |
| Wage differential | Wages of workers in the manufacturing industry (US dollars/hour) in Mexico and the US (Source: INEGI's Economic Information Database). Monthly wages are averaged over quarters and then we take the difference between the US wages and the Mexican wages. I use demeaned and standardized values. | | |
| Distance to border | Distance (kilometers) from the centroid of the respondents municipio to the nearest point of entry along the Mexico-US border. I use the Open Street API to calculate the shortest driving distance between the coordinates. I use demeaned and standardized values. | | |
| Unemployment rate (USA) | I obtain the average quarterly unemployment rate in the USA (Source: FRED). I use national rates as I do not assume specific destinations of migrants. I use demeaned and standardized values. | | |
| Employment rates (Mexico) | State-specific employment rates from INEGI in a given quarter. I use demeaned and standardized values. | | |
| Drought index | I obtain the drought severity index as computed by the Mexican National Weather Service (*Sístema Meteorológico Nacional* (SNM)). It consists of 5 levels: no drought, abnormally dry (D0), moderate drought (D1), severe drought (D2), extreme drought (D3), and exceptional drought (D4). Since this is a monthly index, I choose the value of the last month of the quarter in order to match the temporality of the ENOE. | No drought, D0, D1, D2, D3, and D4 | No drought |

## C.3 Odds ratios for decomposition analysis

| | *Dependent variable: International migrant (0/1)* | | | | | | |
|---|---|---|---|---|---|---|---|
| | International migrant (0/1) | | | | | | |
| | 2005-2006 | 2007-2008 | 2009-2010 | 2011-2012 | 2013-2014 | 2015-2016 | 2017-2019 |
| Intercept | 0.0001*** | 0.006*** | 0.001*** | 0.001*** | 0.001*** | 0.002*** | 0.002*** |
| | (0.00001,0.001) | (0.003,0.012) | (0.0004,0.002) | (0.001,0.002) | (0.001,0.002) | (0.001,0.004) | (0.001,0.004) |
| Female=1 | 0.361*** | 0.320*** | 0.386*** | 0.381*** | 0.434*** | 0.433*** | 0.451*** |
| | (0.333,0.393) | (0.295,0.348) | (0.349,0.428) | (0.340,0.428) | (0.387,0.486) | (0.387,0.484) | (0.410,0.497) |
| Age | 1.097*** | 1.104*** | 1.104*** | 1.113*** | 1.100*** | 1.093*** | 1.077*** |
| | (1.082,1.112) | (1.089,1.118) | (1.087,1.122) | (1.093,1.133) | (1.080,1.120) | (1.073,1.113) | (1.060,1.094) |
| Age squared | 0.999*** | 0.999*** | 0.999*** | 0.999*** | 0.999*** | 0.999*** | 0.999*** |
| | (0.998,0.999) | (0.998,0.999) | (0.999,0.999) | (0.998,0.999) | (0.999,0.999) | (0.999,0.999) | (0.999,0.999) |
| **Place of birth (ref: Mexico)** | | | | | | | |
| USA | 11.742*** | 11.626*** | 21.232*** | 28.119*** | 22.380*** | 16.525*** | 20.589*** |
| | (9.621,14.331) | (9.708,13.922) | (17.970,25.086) | (23.807,33.211) | (18.907,26.490) | (13.792,19.800) | (17.877,23.713) |
| Rest of the World | 6.522*** | 10.273*** | 17.225*** | 12.690*** | 21.816*** | 17.031*** | 12.490*** |
| | (4.530,9.390) | (7.610,13.869) | (13.018,22.791) | (9.036,17.821) | (16.541,28.774) | (12.459,23.279) | (9.403,16.590) |
| **Region in Mexico (ref: Historic migrant sending states)** | | | | | | | |
| North | 0.469*** | 0.578*** | 0.497*** | 0.443*** | 0.480*** | 0.447*** | 0.575*** |
| | (0.415,0.530) | (0.514,0.650) | (0.435,0.569) | (0.383,0.514) | (0.409,0.564) | (0.384,0.520) | (0.508,0.652) |
| Center | 0.627*** | 0.679*** | 0.619*** | 0.558*** | 0.453*** | 0.383*** | 0.552*** |
| | (0.573,0.686) | (0.623,0.740) | (0.543,0.705) | (0.488,0.638) | (0.397,0.518) | (0.335,0.438) | (0.480,0.634) |
| Southeast | 0.458*** | 0.463*** | 0.380*** | 0.396*** | 0.343*** | 0.288*** | 0.370*** |
| | (0.398,0.526) | (0.409,0.523) | (0.320,0.451) | (0.326,0.480) | (0.282,0.418) | (0.234,0.353) | (0.307,0.447) |
| **Size of locality (ref: < 2,500 people)** | | | | | | | |
| 2,500-14,999 | 0.688*** | 0.706*** | 0.719*** | 0.542*** | 0.604*** | 0.586*** | 0.541*** |
| | (0.623,0.758) | (0.643,0.775) | (0.637,0.811) | (0.467,0.629) | (0.518,0.704) | (0.504,0.682) | (0.476,0.614) |
| 15,000-99,999 | 0.519*** | 0.529*** | 0.554*** | 0.500*** | 0.501*** | 0.457*** | 0.332*** |
| | (0.466,0.579) | (0.476,0.588) | (0.484,0.634) | (0.428,0.584) | (0.428,0.586) | (0.392,0.534) | (0.289,0.382) |
| 100,000 + | 0.292*** | 0.317*** | 0.315*** | 0.314*** | 0.318*** | 0.291*** | 0.260*** |
| | (0.269,0.316) | (0.294,0.342) | (0.285,0.348) | (0.281,0.351) | (0.284,0.357) | (0.260,0.327) | (0.236,0.287) |
| **Current education (ref: High school)** | | | | | | | |
| Incomplete elementary | 0.754*** | 0.694*** | 0.716*** | 0.708*** | 0.717*** | 0.690*** | 0.504*** |
| | (0.653,0.871) | (0.609,0.791) | (0.603,0.850) | (0.584,0.858) | (0.586,0.877) | (0.561,0.849) | (0.418,0.607) |
| Complete elementary | 0.935 | 0.860** | 0.856** | 0.815** | 0.871 | 0.794*** | 0.637*** |
| | (0.822,1.063) | (0.767,0.965) | (0.738,0.993) | (0.691,0.960) | (0.736,1.031) | (0.671,0.939) | (0.553,0.734) |
| Complete middle school | 1.057 | 0.943 | 0.945 | 0.976 | 0.917 | 0.930 | 0.834*** |
| | (0.935,1.195) | (0.847,1.050) | (0.823,1.084) | (0.841,1.131) | (0.787,1.069) | (0.802,1.078) | (0.742,0.937) |
| College and above | 0.600*** | 0.542*** | 0.657*** | 0.730*** | 0.837** | 0.917 | 0.876** |
| | (0.516,0.698) | (0.473,0.620) | (0.557,0.775) | (0.613,0.869) | (0.704,0.996) | (0.777,1.083) | (0.768,0.999) |
| **Labor force status (ref: employed)** | | | | | | | |
| Not aplicable | 1.841*** | 1.726*** | 1.773*** | 1.862*** | 1.757*** | 1.693*** | 1.798*** |
| | (1.661,2.040) | (1.560,1.909) | (1.558,2.017) | (1.613,2.150) | (1.514,2.038) | (1.462,1.961) | (1.589,2.035) |
| Unemployed | 0.630*** | 0.716*** | 0.841** | 0.724*** | 0.708*** | 0.909 | 0.815** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (0.543,0.732) | (0.623,0.824) | (0.708,0.998) | (0.595,0.882) | (0.577,0.868) | (0.745,1.108) | (0.693,0.959) |
| Available | 2.457*** | 2.193*** | 2.793*** | 2.897*** | 3.135*** | 3.359*** | 2.592*** |
| | (2.181,2.768) | (1.955,2.459) | (2.407,3.242) | (2.454,3.420) | (2.632,3.734) | (2.821,4.000) | (2.245,2.993) |
| Unavailable | 4.278*** | 3.390*** | 4.394*** | 4.394*** | 6.119*** | 7.312*** | 7.772*** |
| | (2.780,6.583) | (2.151,5.343) | (2.768,6.977) | (2.623,7.361) | (3.939,9.505) | (4.739,11.283) | (5.545,10.894) |
| Has partner=1 | 2.517*** | 2.311*** | 3.195*** | 3.316*** | 3.722*** | 4.561*** | 3.659*** |
| | (1.972,3.214) | (1.800,2.969) | (2.375,4.299) | (2.391,4.600) | (2.671,5.186) | (3.344,6.222) | (2.784,4.810) |
| **Relationship to household head (ref: head of household)** | | | | | | | |
| Spouse/Partner | 0.0003 | 363.983*** | 22.870*** | 0.001 | 30.606*** | 18.519*** | 0.001 |
| | (0.000,Inf) | (236.722,559.659) | (5.507,94.982) | (0.000, Inf) | (8.723,107.386) | (2.526,135.787) | (0.000,Inf) |
| Child | 4.894*** | 3.077*** | 4.820*** | 4.113*** | 5.524*** | 6.397*** | 4.156*** |
| | (4.085,5.863) | (2.564,3.694) | (3.850,6.034) | (3.172,5.333) | (4.276,7.137) | (4.983,8.214) | (3.359,5.142) |
| Parent | 2.452 | 9.486*** | 9.713*** | 5.867*** | 1.980 | 8.288*** | 1.541 |
| | (0.595,10.108) | (4.790,18.783) | (4.469,21.108) | (1.849,18.621) | (0.275,14.270) | (3.030,22.668) | (0.215,11.030) |
| Sibling | 3.860*** | 4.213*** | 5.249*** | 7.844*** | 5.859*** | 4.659*** | 3.341*** |
| | (2.943,5.063) | (3.290,5.395) | (3.821,7.211) | (5.760,10.681) | (4.007,8.567) | (3.104,6.993) | (2.336,4.779) |
| Grandparent | 1.941* | 3.168*** | 2.870** | 4.811*** | 2.456* | 2.636* | 1.954 |
| | (0.978,3.851) | (1.802,5.571) | (1.260,6.536) | (2.333,9.922) | (0.904,6.674) | (0.963,7.217) | (0.795,4.804) |
| Grandchild | 2.441*** | 1.966*** | 2.634*** | 2.149*** | 2.585*** | 3.747*** | 2.340*** |
| | (2.075,2.870) | (1.676,2.306) | (2.160,3.211) | (1.694,2.727) | (2.030,3.291) | (3.011,4.664) | (1.919,2.852) |
| Aunt/Uncle | 1.821*** | 1.656*** | 3.130*** | 4.981*** | 3.563*** | 4.680*** | 2.948*** |
| | (1.343,2.470) | (1.199,2.286) | (2.220,4.413) | (3.588,6.916) | (2.430,5.222) | (3.264,6.711) | (2.081,4.176) |
| Niece/Nephew | 0.328*** | 0.339*** | 0.495*** | 0.463*** | 0.654*** | 0.645*** | 0.597*** |
| | (0.267,0.403) | (0.277,0.416) | (0.382,0.639) | (0.342,0.627) | (0.486,0.880) | (0.478,0.870) | (0.455,0.783) |
| Cousin | 2.118*** | 2.415*** | 1.922*** | 2.234*** | 2.017*** | 2.102*** | 1.714*** |
| | (1.830,2.450) | (2.120,2.750) | (1.640,2.254) | (1.880,2.655) | (1.667,2.439) | (1.727,2.560) | (1.409,2.086) |
| Daughter/Son in-law | 0.905 | 0.961 | 0.804** | 1.112 | 1.064 | 0.917 | 0.773** |
| | (0.780,1.050) | (0.835,1.107) | (0.664,0.973) | (0.917,1.349) | (0.865,1.309) | (0.738,1.141) | (0.633,0.944) |
| Non-family household member | 0.674*** | 0.796*** | 0.799*** | 1.019 | 1.100 | 0.941 | 0.864*** |
| | (0.613,0.741) | (0.728,0.871) | (0.713,0.896) | (0.897,1.157) | (0.969,1.250) | (0.828,1.069) | (0.775,0.964) |
| **Share of household members** | | | | | | | |
| Children (< 18) | 0.670*** | 0.655*** | 0.511*** | 0.583*** | 0.388*** | 0.407*** | 0.487*** |
| | (0.570,0.788) | (0.560,0.767) | (0.415,0.628) | (0.459,0.741) | (0.303,0.498) | (0.318,0.521) | (0.395,0.601) |
| Elderly (> 65) | 0.153*** | 0.376*** | 0.270*** | 0.409*** | 0.366*** | 0.246*** | 0.842 |
| | (0.089,0.263) | (0.235,0.600) | (0.151,0.482) | (0.225,0.741) | (0.204,0.659) | (0.135,0.449) | (0.538,1.315) |
| **Remittances** | | | | | | | |
| Household receives remittances=1 | 4.918*** | 3.693*** | 3.240*** | 3.406*** | 3.070*** | 3.824*** | 3.153*** |
| | (4.593,5.266) | (3.455,3.949) | (2.962,3.544) | (3.072,3.776) | (2.761,3.414) | (3.451,4.238) | (2.879,3.454) |
| Real remittances received (state) | 1.183*** | 1.210*** | 1.145** | 1.095 | 1.019 | 1.004 | 1.064 |
| | (1.122,1.248) | (1.135,1.290) | (1.011,1.297) | (0.965,1.243) | (0.932,1.115) | (0.916,1.101) | (0.985,1.148) |
| **Macroeconomic trends** | | | | | | | |
| US-Mex wage difference | 0.029*** | 1.781* | 0.177*** | 1.093 | 0.396 | 0.939 | 0.381*** |
| | (0.016,0.052) | (0.988,3.211) | (0.081,0.389) | (0.492,2.425) | (0.061,2.589) | (0.541,1.628) | (0.210,0.692) |
| Unemployment rate (US) | 9.336*** | 0.739** | 1.022 | 1.331 | 0.657 | 1.593 | 0.294** |
| | (3.217,27.090) | (0.573,0.955) | (0.820,1.272) | (0.946,1.873) | (0.382,1.131) | (0.440,5.767) | (0.107,0.805) |
| Employment rate (Mex) | 1.080** | 1.015 | 1.046 | 1.005 | 0.947 | 0.974 | 0.957 |
| | (1.012,1.152) | (0.960,1.074) | (0.986,1.110) | (0.933,1.084) | (0.871,1.030) | (0.888,1.069) | (0.885,1.035) |
| Distance to border | 0.684*** | 0.736*** | 0.738*** | 0.698*** | 0.847*** | 0.736*** | 0.780*** |
| | (0.643,0.728) | (0.692,0.782) | (0.683,0.798) | (0.640,0.761) | (0.773,0.929) | (0.669,0.809) | (0.727,0.837) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Drought severity index** | | | | | | | |
| D0 | 1.121*** | 0.922** | 1.037 | 1.077 | 1.064 | 1.073 | 1.097* |
| | (1.030,1.219) | (0.849,1.000) | (0.919,1.170) | (0.950,1.222) | (0.949,1.194) | (0.958,1.202) | (0.998,1.206) |
| D1 | 1.141** | 1.069 | 0.963 | 0.785*** | 1.135 | 1.066 | 1.108* |
| | (1.031,1.262) | (0.979,1.166) | (0.851,1.090) | (0.656,0.939) | (0.900,1.433) | (0.882,1.288) | (0.989,1.241) |
| D2 | 1.306*** | 0.947 | 0.958 | 0.929 | 1.364* | 0.955 | 1.456*** |
| | (1.147,1.487) | (0.824,1.089) | (0.810,1.132) | (0.788,1.095) | (0.967,1.923) | (0.675,1.352) | (1.242,1.708) |
| D3 | 1.426*** | 1.504*** | 0.746 | 0.848* | 2.155*** | 1.372** | 0.836 |
| | (1.173,1.734) | (1.279,1.768) | (0.432,1.287) | (0.706,1.020) | (1.590,2.922) | (1.052,1.788) | (0.589,1.187) |
| D4 | 0.514*** | 0.836 | 0.0004 | 0.937 | 0.00003 | | 1.306 |
| | (0.315,0.838) | (0.502,1.392) | (0.000,Inf) | (0.630,1.395) | (0.000,Inf) | | (0.321,5.323) |
| **Quarter (ref: Q4** | | | | | | | |
| Q1 | 0.468*** | 0.995 | 1.083 | 0.813** | 1.216 | 0.753*** | 1.088 |
| | (0.398,0.551) | (0.879,1.126) | (0.929,1.264) | (0.676,0.977) | (0.889,1.663) | (0.632,0.898) | (0.919,1.288) |
| Q2 | 0.636*** | 0.993 | 1.012 | 1.063 | 1.498*** | 1.011 | 1.403*** |
| | (0.571,0.709) | (0.888,1.110) | (0.878,1.167) | (0.888,1.274) | (1.225,1.832) | (0.834,1.225) | (1.245,1.580) |
| Q3 | 1.016 | 1.125** | 1.546*** | 0.915 | 1.523** | 1.201** | 1.402*** |
| | (0.891,1.158) | (1.010,1.252) | (1.259,1.897) | (0.756,1.108) | (1.092,2.126) | (1.007,1.434) | (1.239,1.586) |
| Observations | 404,528 | 738,991 | 714,196 | 703,547 | 696,886 | 704,244 | 1,039,865 |
| Log Likelihood | -18,207.480 | -22,700.800 | -14,811.940 | -11,809.440 | -11,290.970 | -11,470.000 | -16,030.740 |
| Akaike Inf. Crit. | 36,510.950 | 45,497.610 | 29,719.880 | 23,714.880 | 22,677.930 | 23,034.000 | 32,157.490 |

*Note:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

| | *Dependent variable: International Female Migrant (0/1)* | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2005-2006 | 2007-2008 | 2009-2010 | 2011-2012 | 2013-2014 | 2015-2016 | 2017-2019 |
| Intercept | 0.001*** | 0.002*** | 0.0004*** | 0.0005*** | 0.0002*** | 0.0003*** | 0.0002*** |
| | (0.00004,0.035) | (0.0004,0.006) | (0.0001,0.001) | (0.0002,0.001) | (0.0001,0.0004) | (0.0001,0.001) | (0.0001,0.001) |
| Age | 1.070*** | 1.062*** | 1.070*** | 1.046*** | 1.064*** | 1.061*** | 1.090*** |
| | (1.046,1.095) | (1.040,1.086) | (1.043,1.098) | (1.016,1.076) | (1.035,1.094) | (1.031,1.091) | (1.063,1.117) |
| Age squared | 0.999*** | 0.999*** | 0.999*** | 1.000** | 0.999*** | 0.999*** | 0.999*** |
| | (0.999,1.000) | (0.999,1.000) | (0.999,1.000) | (0.999,1.000) | (0.999,1.000) | (0.999,1.000) | (0.999,0.999) |
| **Place of birth (ref: Mexico)** | | | | | | | |
| USA | 17.263*** | 16.397*** | 29.854*** | 32.696*** | 27.994*** | 25.991*** | 30.997*** |
| | (13.144,22.673) | (12.587,21.361) | (23.396,38.096) | (25.118,42.561) | (21.542,36.378) | (19.899,33.947) | (25.141,38.217) |
| Rest of the World | 6.726*** | 15.662*** | 35.969*** | 15.732*** | 40.782*** | 28.089*** | 21.982*** |
| | (3.485,12.981) | (9.983,24.572) | (24.387,53.052) | (8.875,27.886) | (27.025,61.543) | (17.683,44.619) | (14.632,33.026) |
| **Region in Mexico (ref: Historic migrant sending states)** | | | | | | | |
| North | 0.791** | 0.863 | 0.721*** | 0.684*** | 0.766* | 0.630*** | 0.877 |
| | (0.635,0.984) | (0.692,1.077) | (0.564,0.922) | (0.523,0.895) | (0.585,1.004) | (0.488,0.813) | (0.706,1.090) |
| Center | 0.581*** | 0.674*** | 0.696*** | 0.492*** | 0.362*** | 0.352*** | 0.379*** |
| | (0.483,0.700) | (0.564,0.806) | (0.540,0.897) | (0.373,0.647) | (0.277,0.471) | (0.273,0.455) | (0.290,0.497) |
| Southeast | 0.382*** | 0.441*** | 0.399*** | 0.455*** | 0.278*** | 0.311*** | 0.331*** |
| | (0.288,0.505) | (0.344,0.566) | (0.285,0.560) | (0.315,0.658) | (0.192,0.404) | (0.217,0.445) | (0.238,0.462) |
| **Size of locality (ref: < 2,500 people)** | | | | | | | |
| 2,500-14,999 | 0.845 | 0.734*** | 0.828 | 0.784 | 0.650** | 0.716** | 0.826 |
| | (0.689,1.038) | (0.584,0.924) | (0.637,1.078) | (0.567,1.082) | (0.461,0.915) | (0.531,0.966) | (0.636,1.072) |
| 15,000-99,999 | 0.597*** | 0.765** | 0.739** | 0.838 | 0.899 | 0.594*** | 0.636*** |
| | (0.476,0.750) | (0.608,0.961) | (0.559,0.976) | (0.611,1.150) | (0.669,1.208) | (0.440,0.802) | (0.490,0.825) |
| 100,000 + | 0.402*** | 0.560*** | 0.495*** | 0.565*** | 0.539*** | 0.445*** | 0.482*** |
| | (0.341,0.475) | (0.473,0.662) | (0.404,0.606) | (0.444,0.718) | (0.426,0.683) | (0.355,0.558) | (0.394,0.590) |
| **Current education (ref: High school)** | | | | | | | |
| Incomplete elementary | 0.421*** | 0.408*** | 0.554*** | 0.460*** | 0.527*** | 0.436*** | 0.499*** |
| | (0.314,0.563) | (0.309,0.538) | (0.398,0.769) | (0.309,0.685) | (0.355,0.782) | (0.290,0.653) | (0.349,0.713) |
| Complete elementary | 0.566*** | 0.450*** | 0.551*** | 0.579*** | 0.583*** | 0.617*** | 0.557*** |
| | (0.442,0.724) | (0.354,0.571) | (0.413,0.736) | (0.418,0.803) | (0.417,0.814) | (0.451,0.842) | (0.422,0.737) |
| Complete middle school | 0.716*** | 0.698*** | 0.631*** | 0.697** | 0.764* | 0.620*** | 0.764** |
| | (0.571,0.898) | (0.568,0.858) | (0.488,0.817) | (0.523,0.929) | (0.572,1.019) | (0.469,0.820) | (0.608,0.959) |
| College and above | 0.783* | 0.735*** | 0.797 | 1.013 | 1.138 | 1.210 | 1.105 |
| | (0.607,1.009) | (0.584,0.924) | (0.603,1.054) | (0.752,1.365) | (0.847,1.529) | (0.918,1.595) | (0.878,1.391) |
| **Labor force status (ref: employed)** | | | | | | | |
| Not aplicable | 2.113*** | 1.509*** | 1.755*** | 1.899*** | 1.693*** | 1.351** | 1.271** |
| | (1.735,2.574) | (1.220,1.865) | (1.364,2.256) | (1.440,2.505) | (1.286,2.231) | (1.013,1.801) | (1.004,1.609) |
| Unemployed | 0.447*** | 0.502*** | 0.521*** | 0.399*** | 0.448*** | 0.856 | 0.599*** |
| | (0.328,0.610) | (0.368,0.683) | (0.363,0.750) | (0.266,0.597) | (0.302,0.665) | (0.558,1.312) | (0.428,0.839) |
| Available | 6.003*** | 3.617*** | 4.784*** | 4.530*** | 5.454*** | 6.612*** | 4.459*** |
| | (4.523,7.969) | (2.736,4.782) | (3.394,6.743) | (3.119,6.579) | (3.766,7.900) | (4.442,9.841) | (3.282,6.058) |
| Unavailable | 4.912*** | 4.345*** | 4.020*** | 3.018*** | 4.581*** | 6.310*** | 8.282*** |
| | (2.882,8.373) | (2.580,7.317) | (2.179,7.418) | (1.515,6.012) | (2.575,8.150) | (3.370,11.814) | (5.307,12.925) |
| Has partner=1 | 4.216*** | 3.769*** | 5.124*** | 4.910*** | 4.158*** | 8.556*** | 5.515*** |
| | (2.659,6.684) | (2.423,5.863) | (3.025,8.680) | (2.785,8.654) | (2.272,7.609) | (5.004,14.630) | (3.485,8.727) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Relationship to household head (ref: head of household)** | | | | | | | |
| Spouse/Partner | 0.0001 | 174.611*** | 18.061*** | 0.0001 | 19.352*** | 13.658** | 0.0001 |
| | (0.000,Inf) | (98.347,310.015) | (4.219,77.308) | (0.000,Inf) | (5.185,72.230) | (1.788,104.356) | (0.000,Inf) |
| Child | 18.789*** | 8.421*** | 12.938*** | 7.527*** | 13.441*** | 18.044*** | 10.507*** |
| | (13.146,26.856) | (5.873,12.075) | (8.404,19.917) | (4.547,12.460) | (8.372,21.579) | (11.106,29.316) | (7.101,15.548) |
| Parent | 3.656 | 15.678*** | 20.526*** | 3.855 | 0.00004 | 0.0001 | 0.0001 |
| | (0.495,27.025) | (6.234,39.429) | (7.912,53.249) | (0.499,29.816) | (0.000,Inf) | (0.000,Inf) | (0.000,Inf) |
| Sibling | 9.975*** | 9.157*** | 13.245*** | 16.218*** | 14.154*** | 8.321*** | 5.601*** |
| | (6.096,16.322) | (5.848,14.338) | (7.708,22.760) | (9.451,27.831) | (7.744,25.867) | (3.953,17.514) | (2.944,10.655) |
| Grandparent | 1.430 | 6.911*** | 9.664*** | 6.408** | 4.573** | 8.382*** | 1.851 |
| | (0.195,10.513) | (2.951,16.183) | (3.364,27.762) | (1.529,26.858) | (1.071,19.523) | (1.956,35.916) | (0.252,13.610) |
| Grandparent | 6.045*** | 4.314*** | 5.074*** | 3.346*** | 4.020*** | 8.653*** | 4.800*** |
| | (4.342,8.415) | (3.065,6.070) | (3.390,7.595) | (2.096,5.343) | (2.525,6.400) | (5.472,13.681) | (3.257,7.073) |
| Aunt/Uncle | 3.889*** | 3.028*** | 7.212*** | 9.450*** | 4.916*** | 11.001*** | 6.718*** |
| | (2.271,6.660) | (1.779,5.153) | (4.265,12.195) | (5.539,16.124) | (2.497,9.679) | (5.980,20.236) | (3.958,11.402) |
| Niece/Nephew | 0.862 | 0.849 | 0.848 | 0.808 | 1.462 | 1.274 | 1.466 |
| | (0.588,1.265) | (0.578,1.247) | (0.536,1.343) | (0.470,1.391) | (0.868,2.464) | (0.754,2.154) | (0.926,2.322) |
| Cousin | 1.935*** | 2.737*** | 1.713** | 2.328*** | 2.542*** | 3.266*** | 1.579** |
| | (1.345,2.783) | (2.014,3.719) | (1.128,2.599) | (1.516,3.577) | (1.665,3.882) | (2.217,4.812) | (1.014,2.460) |
| Daughter/Son in-law | 1.581*** | 1.576*** | 1.075 | 1.633*** | 1.830*** | 1.797*** | 0.998 |
| | (1.252,1.997) | (1.245,1.997) | (0.776,1.490) | (1.177,2.267) | (1.313,2.550) | (1.307,2.471) | (0.726,1.371) |
| Non-family household member | 1.115 | 1.286*** | 1.379*** | 1.592*** | 1.759*** | 1.492*** | 1.292*** |
| | (0.951,1.307) | (1.099,1.505) | (1.137,1.674) | (1.277,1.985) | (1.408,2.198) | (1.202,1.852) | (1.084,1.538) |
| **Share of household members** | | | | | | | |
| Children (< 18) | 0.320*** | 0.327*** | 0.276*** | 0.293*** | 0.169*** | 0.296*** | 0.237*** |
| | (0.230,0.446) | (0.234,0.456) | (0.182,0.419) | (0.180,0.477) | (0.104,0.275) | (0.186,0.472) | (0.159,0.354) |
| Elderly (> 65) | 0.086*** | 0.298*** | 0.304*** | 0.354** | 0.202*** | 0.254*** | 0.814 |
| | (0.035,0.216) | (0.133,0.668) | (0.126,0.734) | (0.136,0.917) | (0.077,0.531) | (0.098,0.658) | (0.402,1.646) |
| **Remittances** | | | | | | | |
| Household receives remittances=1 | 2.945*** | 1.855*** | 1.895*** | 1.844*** | 1.905*** | 2.501*** | 1.773*** |
| | (2.576,3.366) | (1.609,2.138) | (1.589,2.261) | (1.501,2.266) | (1.557,2.330) | (2.071,3.021) | (1.490,2.110) |
| Real remittances received (state) | 1.021 | 1.121* | 0.847 | 0.976 | 1.053 | 1.072 | 0.991 |
| | (0.923,1.130) | (0.991,1.270) | (0.666,1.076) | (0.765,1.244) | (0.907,1.221) | (0.908,1.267) | (0.862,1.140) |
| **Macroeconomic trends** | | | | | | | |
| US-Mex wage difference | 0.100*** | 1.484 | 0.367 | 2.075 | 0.003*** | 0.255*** | 0.333** |
| | (0.032,0.314) | (0.465,4.734) | (0.079,1.703) | (0.445,9.685) | (0.0001,0.116) | (0.093,0.697) | (0.116,0.954) |
| Unemployment rate (US) | 79.250*** | 0.826 | 0.889 | 1.313 | 0.180*** | 0.117* | 0.208* |
| | (10.625,591.123) | (0.502,1.358) | (0.588,1.344) | (0.690,2.495) | (0.065,0.496) | (0.012,1.180) | (0.035,1.230) |
| Employment rate (Mex) | 1.050 | 1.030 | 1.107* | 0.868* | 0.938 | 0.942 | 0.978 |
| | (0.924,1.193) | (0.917,1.155) | (0.987,1.242) | (0.751,1.003) | (0.804,1.094) | (0.796,1.115) | (0.848,1.128) |
| Distance to border | 0.835*** | 0.844*** | 0.789*** | 0.786*** | 1.014 | 0.827** | 0.917 |
| | (0.746,0.935) | (0.752,0.949) | (0.685,0.909) | (0.671,0.920) | (0.863,1.192) | (0.703,0.972) | (0.813,1.035) |
| **Drought severity index** | | | | | | | |
| D0 | 1.139 | 0.993 | 1.199 | 1.090 | 1.140 | 1.016 | 1.115 |
| | (0.968,1.341) | (0.840,1.173) | (0.961,1.496) | (0.858,1.384) | (0.924,1.408) | (0.827,1.247) | (0.937,1.326) |
| D1 | 1.095 | 1.320*** | 1.123 | 0.686** | 1.381 | 0.880 | 1.234** |
| | (0.899,1.333) | (1.111,1.570) | (0.889,1.420) | (0.481,0.978) | (0.925,2.063) | (0.620,1.249) | (1.005,1.514) |
| D2 | 1.569*** | 0.859 | 0.983 | 0.997 | 1.928** | 1.016 | 1.670*** |
| | (1.221,2.016) | (0.636,1.161) | (0.712,1.358) | (0.732,1.358) | (1.149,3.237) | (0.553,1.867) | (1.264,2.206) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| D3 | 1.890*** | 2.172*** | 0.796 | 0.982 | 2.438*** | 0.898 | 1.101 |
| | (1.319,2.708) | (1.614,2.924) | (0.286,2.220) | (0.700,1.376) | (1.486,4.000) | (0.552,1.461) | (0.626,1.937) |
| D4 | 0.775 | 1.109 | 0.0003 | 0.902 | 0.00001 | | 2.607 |
| | (0.350,1.716) | (0.402,3.060) | (0.000,Inf) | (0.406,2.006) | (0.000,Inf) | | (0.339,20.034) |
| **Quarter (ref: Q4** | | | | | | | |
| Q1 | 0.281*** | 1.127 | 0.953 | 0.913 | 2.247*** | 0.920 | 1.206 |
| | (0.206,0.383) | (0.884,1.438) | (0.716,1.268) | (0.647,1.289) | (1.279,3.948) | (0.678,1.248) | (0.894,1.627) |
| Q2 | 0.469*** | 0.948 | 0.915 | 0.937 | 2.016*** | 1.005 | 1.274** |
| | (0.379,0.582) | (0.754,1.192) | (0.697,1.202) | (0.662,1.325) | (1.400,2.902) | (0.706,1.430) | (1.020,1.590) |
| Q3 | 0.883 | 1.312** | 1.289 | 0.826 | 2.841*** | 1.120 | 1.653*** |
| | (0.687,1.136) | (1.063,1.619) | (0.867,1.917) | (0.573,1.189) | (1.532,5.269) | (0.815,1.539) | (1.329,2.057) |
| Observations | 208,343 | 381,715 | 367,805 | 361,650 | 358,814 | 362,578 | 536,204 |
| Log Likelihood | -5,419.682 | -6,412.690 | -4,388.394 | -3,514.969 | -3,550.957 | -3,715.623 | -5,192.304 |
| Akaike Inf. Crit. | 10,933.360 | 12,919.380 | 8,870.787 | 7,123.938 | 7,195.915 | 7,523.247 | 10,478.610 |

*Note:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

| | *Dependent variable: International Male Migrant (0/1)* | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2005-2006 | 2007-2008 | 2009-2010 | 2011-2012 | 2013-2014 | 2015-2016 | 2017-2019 |
| Intercept | 0.00001*** | 0.004*** | 0.0004*** | 0.0005*** | 0.001*** | 0.002*** | 0.003*** |
| | (0.00000,0.0001) | (0.002,0.008) | (0.0002,0.001) | (0.0002,0.001) | (0.0004,0.002) | (0.001,0.004) | (0.001,0.005) |
| Age | 1.122*** | 1.143*** | 1.145*** | 1.170*** | 1.143*** | 1.134*** | 1.087*** |
| | (1.103,1.142) | (1.124,1.162) | (1.121,1.170) | (1.142,1.198) | (1.115,1.170) | (1.107,1.162) | (1.065,1.109) |
| Age squared | 0.998*** | 0.998*** | 0.998*** | 0.998*** | 0.998*** | 0.998*** | 0.999*** |
| | (0.998,0.998) | (0.998,0.998) | (0.998,0.998) | (0.998,0.998) | (0.998,0.999) | (0.998,0.999) | (0.999,0.999) |
| **Place of birth (ref: Mexico)** | | | | | | | |
| USA | 7.735*** | 9.060*** | 16.302*** | 25.075*** | 19.619*** | 12.204*** | 15.061*** |
| | (5.771,10.367) | (7.084,11.588) | (12.930,20.554) | (20.189,31.144) | (15.690,24.531) | (9.512,15.657) | (12.383,18.318) |
| Rest of the World | 6.405*** | 7.888*** | 9.229*** | 11.056*** | 13.977*** | 11.932*** | 8.020*** |
| | (4.111,9.977) | (5.272,11.803) | (5.983,14.236) | (7.228,16.913) | (9.551,20.452) | (7.734,18.409) | (5.347,12.029) |
| **Region in Mexico (ref: Historic migrant sending states)** | | | | | | | |
| North | 0.378*** | 0.510*** | 0.429*** | 0.370*** | 0.382*** | 0.375*** | 0.471*** |
| | (0.325,0.439) | (0.444,0.585) | (0.364,0.505) | (0.310,0.442) | (0.312,0.467) | (0.311,0.453) | (0.404,0.549) |
| Center | 0.646*** | 0.683*** | 0.584*** | 0.585*** | 0.486*** | 0.393*** | 0.618*** |
| | (0.582,0.717) | (0.619,0.753) | (0.501,0.680) | (0.501,0.682) | (0.416,0.566) | (0.336,0.461) | (0.525,0.728) |
| Southeast | 0.491*** | 0.466*** | 0.373*** | 0.375*** | 0.364*** | 0.277*** | 0.381*** |
| | (0.417,0.578) | (0.404,0.538) | (0.305,0.455) | (0.298,0.470) | (0.289,0.460) | (0.216,0.355) | (0.304,0.479) |
| **Size of locality (ref: < 2,500 people)** | | | | | | | |
| 2,500-14,999 | 0.654*** | 0.711*** | 0.701*** | 0.489*** | 0.590*** | 0.545*** | 0.481*** |
| | (0.584,0.733) | (0.641,0.788) | (0.612,0.804) | (0.413,0.578) | (0.497,0.700) | (0.457,0.651) | (0.415,0.557) |
| 15,000-99,999 | 0.506*** | 0.493*** | 0.516*** | 0.438*** | 0.402*** | 0.421*** | 0.263*** |
| | (0.446,0.575) | (0.437,0.556) | (0.442,0.604) | (0.366,0.524) | (0.332,0.487) | (0.351,0.505) | (0.221,0.312) |
| 100,000 + | 0.267*** | 0.268*** | 0.270*** | 0.256*** | 0.258*** | 0.245*** | 0.206*** |
| | (0.243,0.294) | (0.245,0.293) | (0.241,0.304) | (0.225,0.292) | (0.225,0.296) | (0.213,0.281) | (0.183,0.231) |
| **Current education (ref: High school)** | | | | | | | |
| Incomplete elementary | 0.888 | 0.803*** | 0.798** | 0.798** | 0.779** | 0.796* | 0.483*** |
| | (0.750,1.052) | (0.690,0.934) | (0.652,0.977) | (0.640,0.995) | (0.616,0.985) | (0.625,1.015) | (0.388,0.601) |
| Complete elementary | 1.081 | 1.018 | 0.994 | 0.902 | 0.970 | 0.847 | 0.639*** |
| | (0.927,1.259) | (0.891,1.163) | (0.834,1.185) | (0.745,1.092) | (0.796,1.182) | (0.693,1.036) | (0.542,0.753) |
| Complete middle school | 1.198** | 1.050 | 1.106 | 1.092 | 0.976 | 1.069 | 0.844** |
| | (1.035,1.388) | (0.925,1.193) | (0.938,1.304) | (0.918,1.300) | (0.813,1.170) | (0.897,1.275) | (0.736,0.968) |
| College and above | 0.508*** | 0.451*** | 0.607*** | 0.599*** | 0.705*** | 0.764** | 0.758*** |
| | (0.420,0.614) | (0.380,0.536) | (0.493,0.747) | (0.481,0.746) | (0.567,0.877) | (0.618,0.944) | (0.644,0.893) |
| **Labor force status (ref: employed)** | | | | | | | |
| Not aplicable | 1.577*** | 1.757*** | 1.687*** | 1.812*** | 1.747*** | 1.722*** | 2.044*** |
| | (1.386,1.796) | (1.553,1.988) | (1.436,1.981) | (1.513,2.169) | (1.445,2.113) | (1.430,2.072) | (1.744,2.397) |
| Unemployed | 2.363*** | 2.518*** | 3.062*** | 2.896*** | 2.793*** | 2.990*** | 2.647*** |
| | (1.944,2.871) | (2.124,2.985) | (2.508,3.740) | (2.313,3.626) | (2.189,3.564) | (2.362,3.785) | (2.200,3.184) |
| Available | 1.893*** | 1.988*** | 2.484*** | 2.617*** | 2.649*** | 2.852*** | 2.251*** |
| | (1.643,2.181) | (1.741,2.270) | (2.090,2.952) | (2.155,3.176) | (2.156,3.255) | (2.324,3.501) | (1.897,2.670) |
| Unavailable | 2.446* | 0.434 | 3.181*** | 3.916*** | 5.256*** | 8.140*** | 4.806*** |
| | (0.981,6.099) | (0.061,3.097) | (1.388,7.290) | (1.584,9.679) | (2.289,12.070) | (4.082,16.232) | (2.446,9.443) |
| Has partner=1 | 2.195*** | 1.965*** | 2.675*** | 2.801*** | 3.566*** | 3.693*** | 3.204*** |
| | (1.630,2.956) | (1.434,2.692) | (1.846,3.875) | (1.852,4.236) | (2.379,5.346) | (2.470,5.522) | (2.253,4.556) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Relationship to household head (ref: head of household)** | | | | | | | |
| Spouse/Partner | 0.001 | 542.110*** | 0.001 | 0.001 | 0.0002 | 0.003 | 0.002 |
| | (0.000,Inf) | (269.191,1,091.727) | (0.000,Inf) | (0.000,Inf) | (0.000,Inf) | (0.000,Inf) | (0.000,Inf) |
| Child | 3.016*** | 2.299*** | 3.396*** | 3.576*** | 3.874*** | 4.525*** | 2.930*** |
| | (2.407,3.779) | (1.836,2.878) | (2.562,4.500) | (2.611,4.897) | (2.812,5.338) | (3.313,6.179) | (2.238,3.836) |
| Parent | 1.918 | 6.431*** | 3.653* | 6.136** | 3.646 | 12.645*** | 2.485 |
| | (0.260,14.166) | (2.322,17.810) | (0.874,15.261) | (1.471,25.593) | (0.499,26.634) | (4.507,35.474) | (0.344,17.966) |
| Sibling | 2.865*** | 3.324*** | 3.740*** | 5.993*** | 3.773*** | 4.073*** | 3.001*** |
| | (2.045,4.012) | (2.441,4.527) | (2.474,5.653) | (4.031,8.910) | (2.239,6.360) | (2.476,6.701) | (1.938,4.646) |
| Grandparent | 2.092* | 2.332** | 1.352 | 4.720*** | 1.835 | 1.739 | 2.147 |
| | (0.998,4.388) | (1.084,5.016) | (0.332,5.503) | (2.041,10.915) | (0.450,7.491) | (0.424,7.128) | (0.784,5.882) |
| Grandchild | 1.754*** | 1.579*** | 2.086*** | 1.865*** | 2.317*** | 3.110*** | 2.012*** |
| | (1.417,2.171) | (1.290,1.933) | (1.623,2.682) | (1.386,2.510) | (1.725,3.112) | (2.372,4.077) | (1.573,2.573) |
| Aunt/Uncle | 1.562** | 1.350 | 1.785** | 3.512*** | 3.629*** | 3.418*** | 2.048*** |
| | (1.068,2.284) | (0.883,2.066) | (1.044,3.052) | (2.233,5.523) | (2.274,5.791) | (2.115,5.521) | (1.245,3.367) |
| Niece/Nephew | 0.254*** | 0.303*** | 0.511*** | 0.511*** | 0.629** | 0.688* | 0.482*** |
| | (0.196,0.330) | (0.234,0.392) | (0.369,0.707) | (0.348,0.750) | (0.429,0.922) | (0.471,1.007) | (0.338,0.688) |
| Cousin | 2.191*** | 2.409*** | 1.993*** | 2.257*** | 1.999*** | 1.916*** | 1.857*** |
| | (1.863,2.576) | (2.084,2.786) | (1.677,2.369) | (1.869,2.726) | (1.615,2.475) | (1.522,2.412) | (1.491,2.313) |
| Daughter/Son in-law | 0.862 | 1.033 | 0.988 | 1.321** | 1.135 | 0.822 | 0.929 |
| | (0.704,1.055) | (0.861,1.239) | (0.776,1.258) | (1.031,1.692) | (0.859,1.500) | (0.595,1.135) | (0.714,1.209) |
| Non-family household member | 0.625*** | 0.823*** | 0.727*** | 1.066 | 1.156* | 1.000 | 0.932 |
| | (0.548,0.714) | (0.730,0.928) | (0.618,0.856) | (0.897,1.266) | (0.973,1.373) | (0.837,1.194) | (0.800,1.086) |
| **Share of household members** | | | | | | | |
| Children (< 18) | 0.879 | 0.787** | 0.623*** | 0.714** | 0.513*** | 0.451*** | 0.610*** |
| | (0.726,1.063) | (0.655,0.945) | (0.488,0.796) | (0.539,0.945) | (0.382,0.689) | (0.335,0.605) | (0.474,0.784) |
| Elderly (> 65) | 0.169*** | 0.329*** | 0.168*** | 0.296*** | 0.369** | 0.189*** | 0.759 |
| | (0.086,0.331) | (0.183,0.592) | (0.076,0.368) | (0.135,0.651) | (0.171,0.798) | (0.085,0.418) | (0.420,1.372) |
| **Remittances** | | | | | | | |
| Household receives remittances=1 | 5.834*** | 4.614*** | 3.935*** | 4.309*** | 3.861*** | 4.674*** | 4.102*** |
| | (5.383,6.324) | (4.272,4.984) | (3.543,4.370) | (3.820,4.861) | (3.405,4.378) | (4.133,5.286) | (3.684,4.569) |
| Real remittances received (state) | 1.252*** | 1.243*** | 1.262*** | 1.123 | 1.003 | 0.977 | 1.090* |
| | (1.175,1.335) | (1.153,1.341) | (1.090,1.461) | (0.967,1.304) | (0.895,1.124) | (0.875,1.092) | (0.994,1.196) |
| **Macroeconomic trends** | | | | | | | |
| US-Mex wage difference | 0.017*** | 1.853* | 0.131*** | 0.865 | 2.599 | 1.648 | 0.433** |
| | (0.008,0.035) | (0.931,3.688) | (0.052,0.329) | (0.339,2.203) | (0.277,24.358) | (0.849,3.197) | (0.209,0.897) |
| Unemployment rate (US) | 4.175** | 0.714** | 1.059 | 1.342 | 1.100 | 5.160** | 0.386 |
| | (1.169,14.911) | (0.529,0.963) | (0.817,1.374) | (0.896,2.012) | (0.576,2.098) | (1.087,24.502) | (0.113,1.320) |
| Employment rate (Mex) | 1.071* | 1.011 | 1.025 | 1.070 | 0.953 | 0.987 | 0.949 |
| | (0.992,1.155) | (0.948,1.078) | (0.957,1.098) | (0.980,1.169) | (0.862,1.053) | (0.883,1.103) | (0.863,1.042) |
| Distance to border | 0.635*** | 0.710*** | 0.727*** | 0.671*** | 0.788*** | 0.693*** | 0.728*** |
| | (0.590,0.685) | (0.661,0.763) | (0.662,0.798) | (0.606,0.744) | (0.704,0.881) | (0.616,0.780) | (0.667,0.794) |
| **Drought severity index** | | | | | | | |
| D0 | 1.102* | 0.903** | 0.959 | 1.089 | 1.036 | 1.103 | 1.080 |
| | (0.998,1.217) | (0.822,0.992) | (0.830,1.108) | (0.939,1.263) | (0.903,1.188) | (0.962,1.264) | (0.964,1.210) |
| D1 | 1.134** | 0.999 | 0.898 | 0.826* | 1.057 | 1.161 | 1.051 |
| | (1.007,1.277) | (0.902,1.106) | (0.776,1.040) | (0.670,1.018) | (0.793,1.408) | (0.927,1.455) | (0.916,1.205) |
| D2 | 1.224*** | 0.983 | 0.949 | 0.907 | 1.010 | 0.953 | 1.340*** |
| | (1.050,1.426) | (0.839,1.152) | (0.780,1.154) | (0.746,1.102) | (0.628,1.624) | (0.624,1.455) | (1.102,1.630) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| D3 | 1.281** | 1.313*** | 0.709 | 0.806* | 1.955*** | 1.585*** | 0.709 |
| | (1.013,1.620) | (1.079,1.598) | (0.372,1.353) | (0.647,1.003) | (1.323,2.889) | (1.153,2.179) | (0.453,1.111) |
| D4 | 0.455** | 0.768 | 0.0001 | 0.975 | 0.00002 | | 0.934 |
| | (0.244,0.849) | (0.423,1.392) | (0.000,Inf) | (0.615,1.546) | (0.000,Inf) | | (0.128,6.817) |
| **Quarter (ref: Q4** | | | | | | | |
| Q1 | 0.560*** | 0.948 | 1.148 | 0.772** | 0.957 | 0.695*** | 1.031 |
| | (0.462,0.680) | (0.821,1.095) | (0.955,1.379) | (0.620,0.961) | (0.655,1.398) | (0.560,0.862) | (0.840,1.266) |
| Q2 | 0.699*** | 0.984 | 1.069 | 1.128 | 1.361** | 1.022 | 1.470*** |
| | (0.615,0.795) | (0.865,1.120) | (0.903,1.265) | (0.912,1.395) | (1.068,1.734) | (0.812,1.286) | (1.276,1.694) |
| Q3 | 1.064 | 1.077 | 1.691*** | 0.960 | 1.210 | 1.236* | 1.293*** |
| | (0.910,1.244) | (0.950,1.220) | (1.329,2.150) | (0.766,1.203) | (0.812,1.803) | (0.998,1.531) | (1.113,1.502) |
| Observations | 196,185 | 357,276 | 346,391 | 341,897 | 338,072 | 341,666 | 503,661 |
| Log Likelihood | -12,323.120 | -15,720.470 | -10,069.250 | -8,022.233 | -7,477.281 | -7,523.583 | -10,486.590 |
| Akaike Inf. Crit. | 24,740.240 | 31,534.950 | 20,232.510 | 16,138.470 | 15,048.560 | 15,139.170 | 21,067.190 |

*Note:* $^{*}p < 0.1; ^{**}p < 0.05; ^{***}p < 0.01$

## C.4 Predicted counts of migrants

**Figure C.1:** Predicted counts of migrants by sex from models estimated between 2005 and 2008.

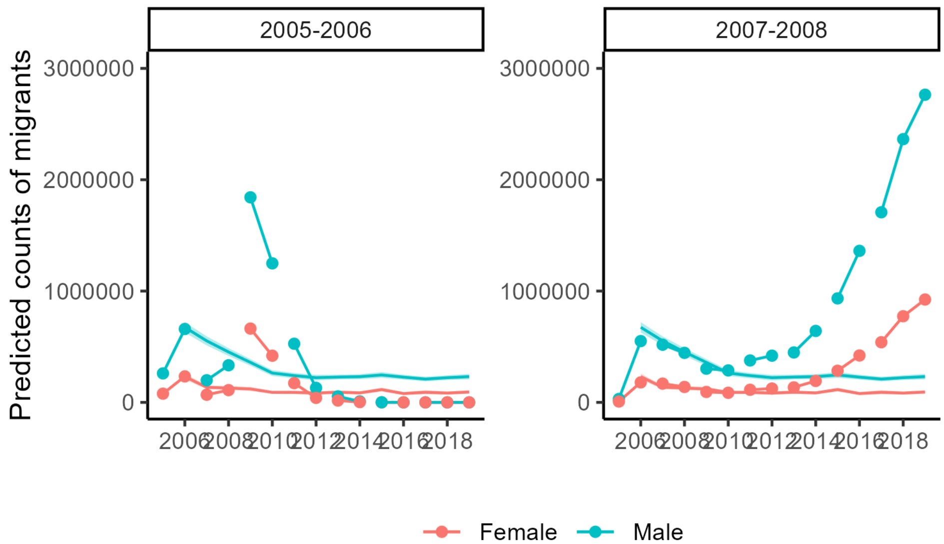


**Figure C.2:** Predicted counts of migrants by sex from models estimated between 2009 and 2012.

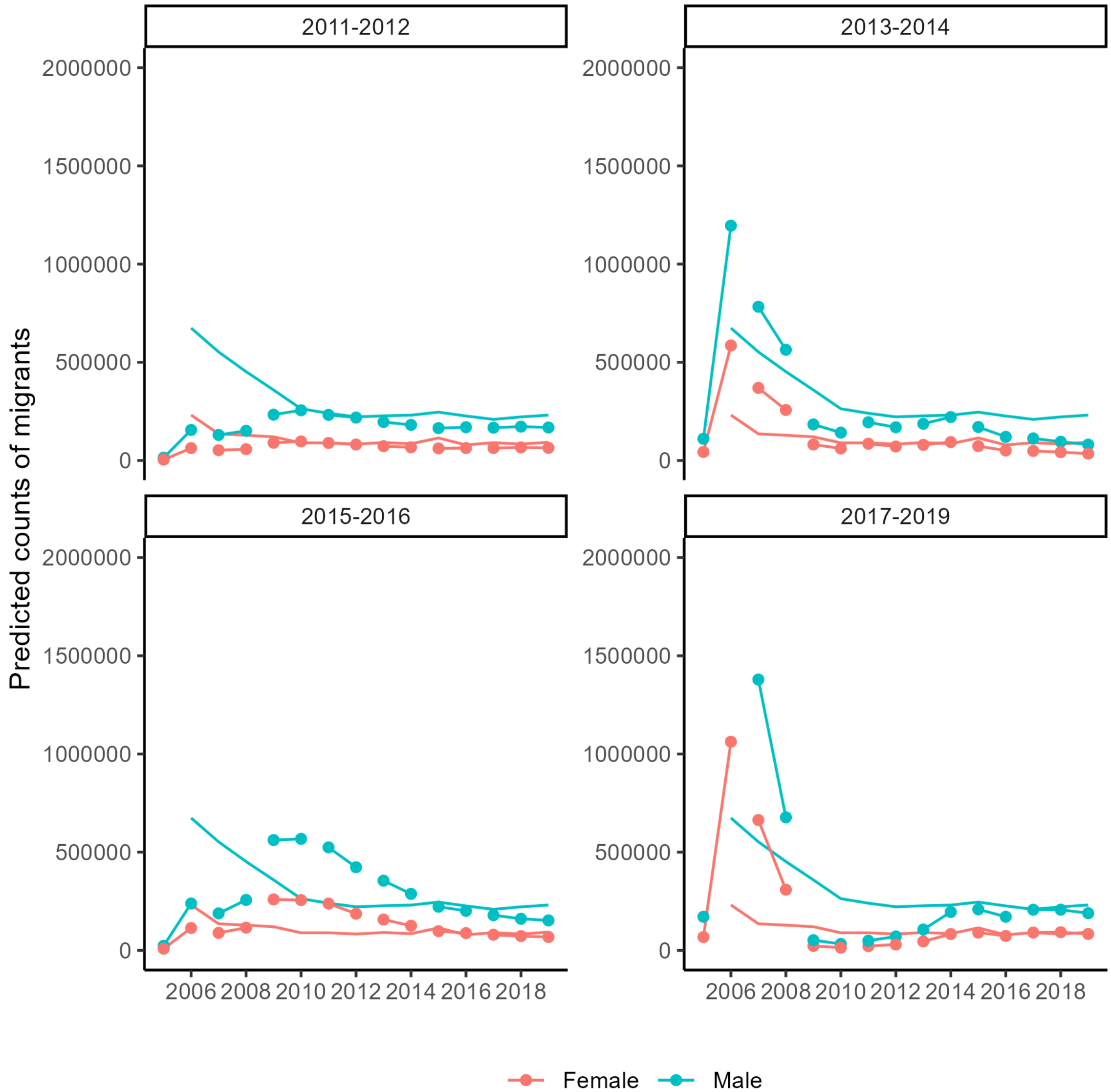


**Figure C.3:** Predicted counts of migrants by sex from models estimated between 2013 and 2019.

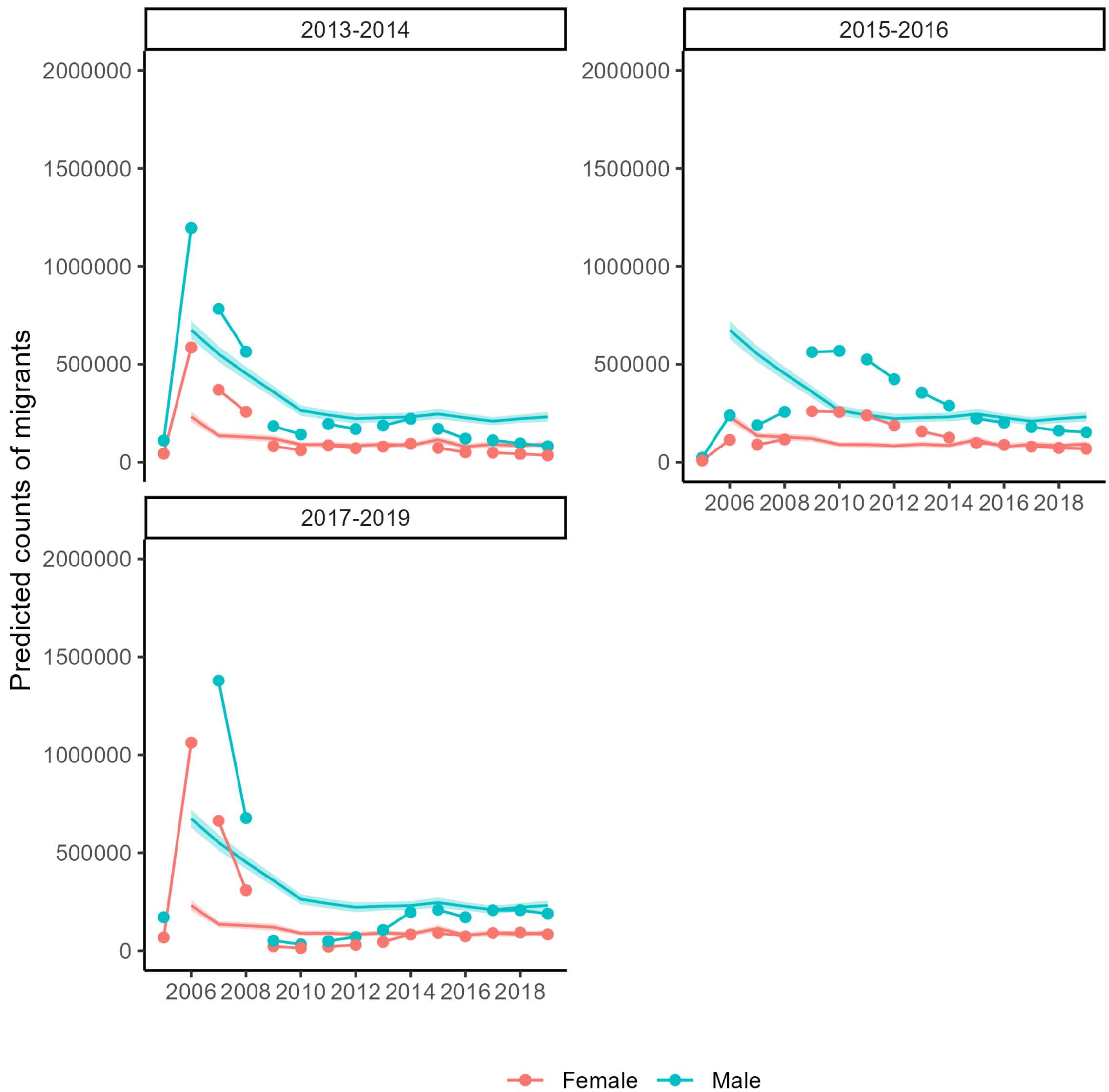


**Figure C.4:** Predicted counts of migrants by sex from sex-specific models estimated in two-year periods.

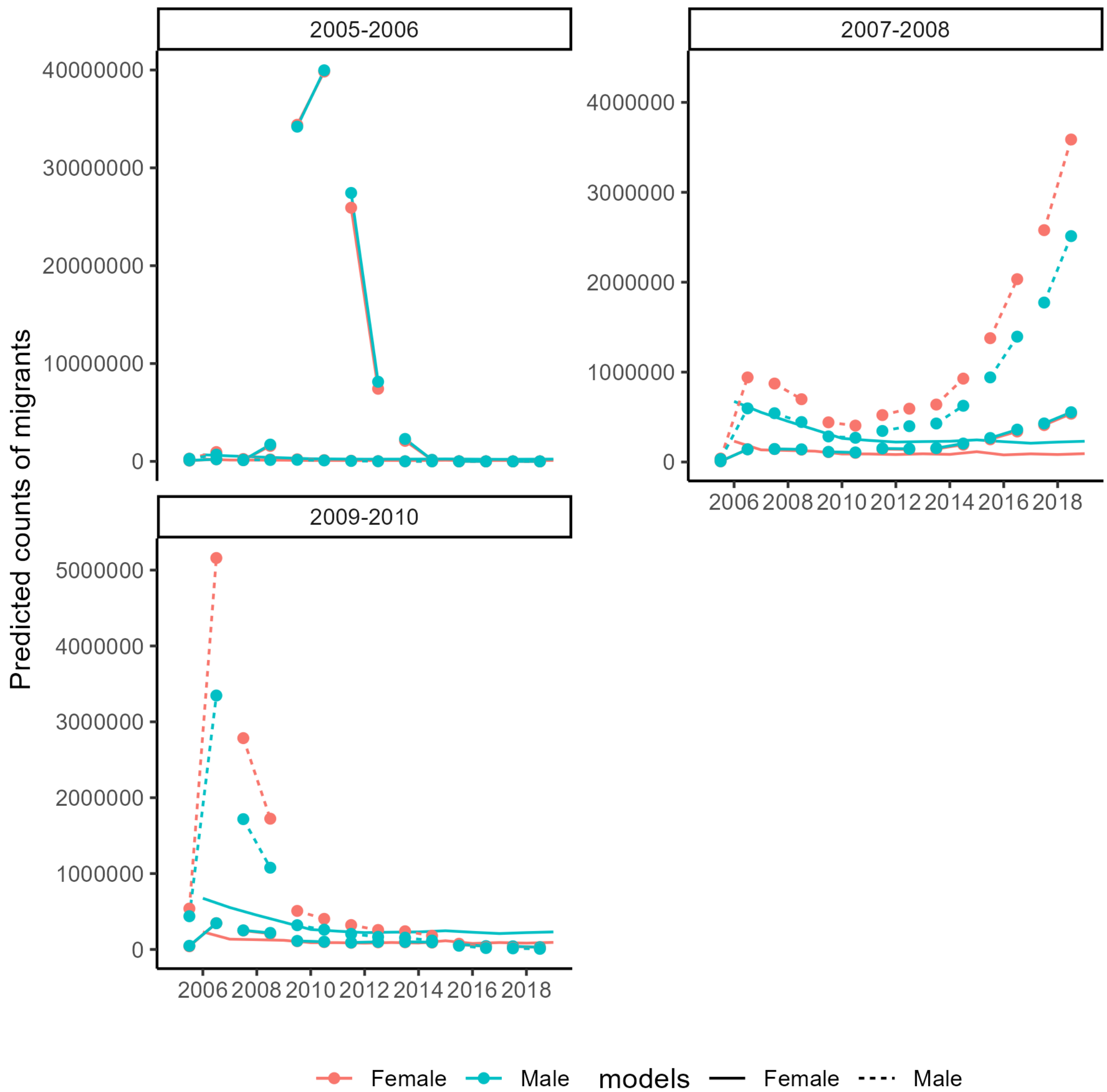


**Figure C.5:** Predicted counts of migrants by sex from sex-specific models estimated in two-year periods.