EL COLEGIO DE MÉXICO, A.C.
CENTRO DE ESTUDIOS ECONÓMICOS

THREE ESSAYS ON MEXICO - US MIGRATION: SELF-SELECTION CHARACTERIZATION, RISK AVERSION AND THE IMPACT ON THE SOCIAL SECURITY AND WELFARE SYSTEM.

TESIS PRESENTADA POR

LUIS FELIPE PÉREZ GÓMEZ

PROMOCIÓN 2020-2023

CIUDAD DE MÉXICO JUNIO DE 2025

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DOCTOR EN ECONOMÍA

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DIRECTOR DE TESIS

DR. JAIME SEMPERE CAMPELLO

CIUDAD DE MÉXICO

JUNIO DE 2025

EL COLEGIO DE MÉXICO

CENTRO DE ESTUDIOS ECONÓMICOS

CONSTANCIA DE APROBACIÓN

Doctorante: Luis Felipe Pérez Gómez

Tesis: *Three Essays on Mexico - US Migration: Self-selection Characterization, Risk Aversion and the Impact on the Social Security and Welfare System.*

Director de Tesis: Dr. Jaime Sempere Campello

Aprobada por el Jurado Examinador:

Dr. Jaime Sempere Campello	Presidente	______________________
Dr. Daniel Isaac Chiquiar Cikurel	Primer Vocal	______________________
Dr. José Jorge Mora Rivera	Vocal Secretario	______________________
Dr. Stephen McKnight	Suplente	______________________

Ciudad de México, 20 de junio de 2025

Dedicada a mi madre, Hilda, y a mi padre, Luis Rodolfo.

Acknowledgments

Agradezco profundamente al profesor Jaime Sempere y a los integrantes de mi comité, el profesor Daniel Chiquiar y el profesor Jorge Mora, por su acompañamiento a lo largo de este proceso. Su guía generosa, sus observaciones rigurosas y su constante disposición para compartir conocimientos han sido fundamentales para el desarrollo de esta tesis. Más allá de su papel académico, han sido y siguen siendo grandes mentores, cuya influencia ha marcado mi formación profesional y personal.

Al Colegio de México, a su comunidad y personal, que se han consolidado como un espacio privilegiado para desarrollar investigción y que siempre muestra apoyo para facilitarla.

Con un profundo agradecimiento, por el apoyo y buena vibra durante el proceso, para: Ale, Tona, Borre, Aymara, Sol, Luis Mario, David y Leila. Ellas son las personas que han sido un soporte importate en los momentos difíciles. Les quiero y menciono por orden de aparición en la vida.

A todas las personas que se mantuvieron constantes en el proceso y aguantaron la intensidad de mis explicaciones, siempre mostrandome interés y en algunos casos retroalimentación.

Contents

Introduction

This thesis examines the evolving migration dynamics between Mexico and the United States through three empirical chapters that explore selection mechanisms, individual risk profiles, and fiscal impacts. By leveraging large-scale survey data and incorporating recent theoretical advances, it seeks to deepen our understanding of how economic and policy shocks influence migration decisions and outcomes. The three chapters respectively address the role of risk aversion in self-selection, the temporal evolution of selection patterns, and the fiscal implications of Mexican migration for the U.S. social security and welfare systems.

Chapter I introduces a novel framework for analyzing migration self-selection by incorporating an ex-ante measure of individual risk aversion. Using data from the Mexican National Employment and Occupation Survey (ENOE), it demonstrates how migrants' decisions reflect heterogeneous behavioral profiles—specifically, risk-averse and risk-tolerant individuals—and how these profiles shape the self-selection process. By leveraging kernel density estimations of log-income distributions for migrants and non-migrants across risk profiles, the analysis reveals distinct selection patterns. Risk-averse individuals tend to display more systematic positive selection, while risk-takers show greater heterogeneity and less consistent patterns. This framework contributes to the literature by integrating behavioral traits such as risk tolerance into the analysis of migration dynamics, extending beyond traditional models that focus solely on economic or demographic factors.

Chapter II expands this analysis by examining how self-selection patterns change over time in response to economic and political shocks—namely the 2008–2009 global financial crisis and Mexico's 2012 presidential transition. This chapter distinguishes between observable and unobservable characteristics and disaggregates the analysis by risk aversion profile. The results indicate that selection is not static: while risk-averse individuals exhibit recurring patterns of positive selection in observable skills—especially during periods of economic instability—unobservable characteristics yield more ambiguous signals. For risk-takers, observable selection patterns fluctuate more sharply, reflecting the influence of shifting incentives, while unobservable traits offer limited consistency. These findings reinforce the relevance of Fernández-Huertas (2011) and G. H. Hanson and Liu (2021) in highlighting that selection patterns are both context-specific and shaped by non-economic factors such as social networks and perceived risk. The chapter concludes that incorporating behavioral heterogeneity through risk profiles enhances our ability to model and understand the complexity of migration decisions.

Chapter III turns to the fiscal impact of Mexican migrants on the U.S. social security and welfare systems from 2007 to 2017. By applying two complementary methods—one based on the Current Population Survey (CPS) and another integrating Congressional Budget Office (CBO) data—the analysis quantifies the net fiscal contributions of Mexican migrants. The results reveal persistent deficits among Mexican migrants, particularly undocumented ones, primarily due to limited access to formal employment and tax contribution mechanisms. However, differences by legal status, gender, and time horizon point to the importance of targeted policy responses that promote labor market inclusion and legal pathways to improve fiscal alignment.

Altogether, the thesis offers a multi-dimensional view of migration between Mexico and the U.S., drawing on labor economics, behavioral modeling, and fiscal analysis. By integrating concepts such as risk aversion and selection across time, it provides a more robust framework for understanding migration flows and their implications. The findings underscore the need for migration and labor policies that are adaptive, evidence-based, and sensitive to both individual characteristics and broader contextual changes.

Chapter I. Risk Aversion and Migration: A self-selection Characterization Based on Risk Aversion Profiles.

Abstract

This chapter revisits the Borjas model of migration self-selection by incorporating an ex-ante measure of individual risk aversion to analyze how behavioral profiles influence migration decisions between Mexico and the United States. Using data from the National Occupation and Employment Survey (ENOE) from 2007 to 2017, the study compares income distributions of migrants and non-migrants across risk-averse and risk-taker groups. The analysis reveals heterogeneous selection patterns over time and across subgroups. Risk-averse individuals tend to show signs of positive selection, migrating when expected returns justify perceived risks. In contrast, selection among risk-takers is more ambiguous, with no consistent pattern emerging across the income distribution. Gender-based disaggregation highlights further differences in selection dynamics, suggesting that both individual preferences and contextual constraints shape migration outcomes. These findings provide new empirical insights into how risk preferences condition migration decisions and contribute to refining self-selection models in migration theory. The implications of these dynamics are relevant for labor market analysis and the design of migration and social policy.

Key concepts: self-selection; migration; human capital; skills; Mexico-USA ; risk aversion.

JEL classification: J31, J61, O15, R23.

Introduction

Migration dynamics have been the subject of intense research due to their significant economic, social, and political implications. Migration, when framed as an economic phenomenon, is often viewed as a human capital investment decision (Sjaastad, 1962), where individuals weigh potential benefits, such as higher wages and better economic prospects, against the costs and risks of relocation. This perspective allows for a deeper understanding of migration as a calculated decision, where individuals aim to maximize their returns by choosing to migrate when expected benefits outweigh the costs.

This research focuses on Mexican migration to the U.S., a context that has experienced significant changes in migration dynamics in recent decades. Mexico has evolved from being primarily a sending country to becoming a temporary host and, increasingly, a permanent destination for migrants. This shift has had profound effects on Mexico's labor markets, altering how individuals evaluate local labor conditions and the potential gains from migration. According to G. Hanson et al. (2023), the evolving U.S. immigration policies and the ongoing economic instability in Latin American countries, particularly Central America and Venezuela, have increased the costs and risks of migration. As a result, Mexico has become a final destination or long-term residence for many migrants, reshaping the migration decision-making process for Mexicans as they consider whether to migrate or remain in a more competitive labor market.

Between 2007 and 2017, the number of Mexican migrants to the U.S. saw notable shifts, with the percentage of male migrants decreasing more steeply than females, highlighting how specific economic and social pressures influence migration demographics. Additionally, Mexico's role as a host country for asylum seekers has grown, creating pressure on labor markets as these individuals, along with refugees and other migrants, integrate into formal and informal sectors. This situation affects Mexicans contemplating migration to the U.S., impacting their risk aversion as they assess new labor dynamics at home. This research investigates how such changes in migrant composition and risk tolerance influence both labor markets and public policy, contributing to the discourse on migration and economic integration across both countries.

Building upon established migration models, this research incorporates an ex-ante risk aversion measure to refine the self-selection characterization of Mexican migrants. This approach sheds light on how personal risk tolerance and contextual pressures, including the economic impact of incoming asylum seekers and refugees, influence migration decisions. For example, by 2017, a 72% decrease in migrants from the 2007 levels and a subsequent increase of 92% from 2012 to 2017 illustrate how economic conditions affect migration patterns over time. As risk perceptions shift in response to labor market competition, the study anticipates changes in the distribution of migrants and non-migrants, along with evolving selection biases. Using recent data and a risk-based analytical framework, this research offers insights into the broader economic landscape, contributing both theoretical depth and practical policy recommendations for managing migration impacts on Mexican and U.S. labor markets.

The chapter hypothesizes that self-selection bias in migration dynamics between Mexico and the U.S. can be more accurately characterized by incorporating an ex-ante measure of risk aversion, thereby refining our understanding of the decision-making processes of individuals considering migration based on varying levels of risk tolerance. Additionally, it is proposed that the changing economic and social context —such as shifts in wage structures, migrant inflows, and labor market conditions— impacts both the distribution and composition of migrant and non-migrant groups, further influencing selection biases within the migration decision-making framework. By applying stochastic dominance criteria, the study aims to reveal how selection bias varies based on the risk aversion, potentially demonstrating that higher risk aversion correlates with distinct migration outcomes across these groups.

Durand et al. (2001) highlight the historical continuity in Mexican migration to the U.S., particularly from the western states of Guanajuato, Jalisco, and Michoacán. Their research shows that despite changing economic and social conditions, the same regions in Mexico have consistently contributed the largest share of migrants over time. This stability, combined with the expansion of migrant networks, has led to a less selective migration flow over time, with education levels becoming more varied among migrants.

The impact of immigration on economic growth and labor markets has been widely explored. Borjas (1995b) identified key factors such as skill levels, policy environments, and economic conditions in the host country as critical to the outcomes of the immigrant labor market. Borjas (2019) further expanded this analysis, showing that while immigration increases overall GDP by expanding the labor force, continuous flows of low-skilled migrants can reduce per capita income. In contrast, high-skilled migrants improve productivity and promote innovation. Abramitzky and Boustan (2017) provided a historical review, showing that although immigrant selection patterns have shifted from mixed to positive, neither group of immigrants has fully caught up economically with native-born Americans within a single generation. Borjas (1995a) estimated that immigration contributes modestly to the U.S. economy, with a 0. 1% increase in GDP, while simultaneously increasing income inequality.

Borjas (1991) study on immigrant self-selection built on his earlier work (1987) by introducing a model that explains how income differentials between origin and destination countries shape migration decisions. High-skilled individuals from countries with less income inequality are more likely to migrate, as they are drawn to better opportunities, while low-skilled individuals from more unequal societies migrate due to greater economic disparities. This mechanism is particularly relevant in contexts like Mexico-U.S. migration, where the wage gap and economic returns to skills can drive self-selection.

Similarly, Grogger and Hanson (2011) examines how income considerations shape migration patterns, focusing on education levels and destination choices. Using the Roy model of income maximization and data on migrant stocks in OECD countries, the study finds that migrants are positively selected (more educated than non-migrants) and tend to sort into countries with higher returns to skill, such as the U.S. and Canada, where wage disparities between high - and low-skilled workers are greater. Absolute wage differences, rather than relative ones, better explain migration patterns, and post-tax wages are strongly correlated with skilled migration. Migration costs, often significantly higher for low-skilled workers, and policies like visa requirements and tax systems also influence decisions. The study highlights the dominant role of economic incentives in shaping migration flows while acknowledging data limitations and policy effects. G. H. Hanson and Liu (2021) highlighted that the quality of education in migrants' origin countries influences their sorting into occupations in the U.S., with high-skilled immigrants from countries with strong educational systems clustering in cognitive-demanding jobs.

However, Ibarraran and Lubotsky (2005) found that Mexican migrants to the U.S. tend to be negatively selected in terms of educational attainment compared to non-migrants, challenging previous assumptions that migration primarily attracts high-skilled workers. This highlights the complex dynamics between economic conditions in the source country and migrant selection, where financial constraints, economic disparities, and the level of education significantly influence who migrates.

Boubtane et al. (2016) supported these findings, demonstrating that immigration contributes positively to GDP per capita, particularly in countries with selective immigration policies. However, they emphasized that higher-skilled migrants have a more significant impact on long-term growth. Borjas et al. (1992) further explored the role of family reunification in shaping the skill composition of migrants, showing that family migration policies can reduce the positive self-selection of immigrants, affecting their labor market outcomes. The general consensus is that while immigration boosts GDP and addresses labor shortages, the benefits are unevenly distributed, particularly based on the skill level of the migrants (Borjas, 2019).

Self-selection is a key concept in migration research, particularly in the study of Mexico-U.S. migration. Borjas (1987) was the first to theoretically apply the self-selection model, based on the Roy model, to examine how differences in income inequality between origin and destination countries influence migration patterns. The first empirical test of this theory, which compared the wage distribution of Mexican migrants and non-migrants, was later conducted by Chiquiar and Hanson (2005). Later, Fernández-Huertas (2011) introduced a new methodology to assess self-selection biases, finding that Mexican migrants had lower skill levels than those who remained in Mexico, supporting the negative selection hypothesis. However, Chiquiar and Hanson (2005) argued that Mexican migrants tend to come from the middle of the income distribution, suggesting intermediate rather than negative selection.

Belot and Hatton (2012) added a broader international perspective to the self-selection literature with their study on immigrant selection in OECD countries. Using a variant of the Roy model, they found that educational selectivity is often shaped more by cultural similarities, colonial legacies, and geographic proximity than by wage incentives or immigration policies. Their research also highlighted the role of poverty in source countries, which prevents lower-educated individuals from migrating, contributing to positive selection and a "brain drain" from poor to rich countries. This suggests that financial constraints, along with economic incentives, play a significant role in determining the skill composition of migrants, a dynamic that is crucial for understanding migration from Mexico to the U.S. and other countries.

Migration networks also play a critical role in the formation of self-selection. McKenzie et al. (2010) argued that strong migration networks lower migration costs, promoting negative self-selection by enabling lower-skilled individuals to migrate. Munshi (2003) also highlighted the importance of social networks in facilitating employment for migrants, showing that while networks help reduce initial migration costs, they may also limit long-term economic integration by leading to demographic and economic concentration. These networks shape expectations and influence migration decisions, both in the home and host countries, making them a critical factor in understanding the returns on human capital investment.

The relationship between migration and wage inequality is well documented. Borjas (1999) showed that low-skilled immigration suppresses wages for native low-skilled workers, while Autor et al. (2008) found that skill-biased technological change has been a major driver of wage inequality. Wage polarization, driven by the rising demand for high-skilled jobs and a decline in middle-wage employment, has disproportionately affected low-skilled workers. Dustmann et al. (2022) explored this issue in the UK, finding that while immigration slightly lowers wages at the lower end of the distribution, it increases wages for high-skilled workers. Borjas (2019) emphasized that high-skilled immigrants can mitigate wage polarization by fostering innovation, whereas low-skilled immigration tends to suppress wages, benefiting capital owners but challenging wage equity.

Family dynamics also play a central role in migration decisions. Borjas and Bratsberg (1996) examined how family ties influence the decision to migrate, noting that previous family migration experiences shape current migration choices. Mora-Rivera and Fierros-González (2020) found that socioeconomic factors, particularly among low-income populations, significantly impact migration dynamics. Lessem (2017) demonstrated that border enforcement policies also affect migration flows, as stricter enforcement prevents both inflows and outflows, leading to longer durations of stay for temporary migrants.

Education is another important factor influencing migration. Ibarraran and Lubotsky (2005) found that Mexican migrants to the U.S. tend to be less educated than non-migrants, supporting the theory of negative selection. However, Kaestner and Malamud (2014) identified a more complex pattern, finding both positive and negative selection depending on the context. Borjas (1991) explained that income inequality between countries influences this self-selection, with high-skilled individuals more likely to migrate from less unequal societies, while low-skilled individuals migrate due to greater economic disparities.

Financial constraints also shape migration decisions. Angelucci (2012) showed how alleviating financial restrictions through cash transfers increases migration flows, particularly for lower-skilled individuals. This aligns with Caponi (2011) findings on the U-shaped relationship between education and migration, where the least educated and most educated individuals are more likely to migrate, each driven by different economic incentives.

This chapter aims to apply these theoretical and empirical insights to the Mexico-U.S. migration context. Using data from Mexico's National Occupation and Employment Survey (ENOE, for its Spanish acronym), to analyze self-selection patterns by comparing migrants and non-migrants prior to migration, following the methodology of Fernández-Huertas (2011) and Borjas et al. (2018). The study will also explore the role of risk aversion in shaping migration decisions, contributing to a deeper understanding of the factors driving Mexican migration to the U.S. and how self-selection patterns have changed in the Mexico U.S. migration dynamics, given the changes in the context and all the factors that interfere in the migration decision. The main idea is to test if the negative selection bias still holds or if the changes in the context where individuals make the decision process influence a change in the self-selection patterns. In this sense, it is expected that the changes in Mexico's context have an effect on the latter, and in the sense of Chiquiar and Hanson (2005) positive selection is going to be found in more group profiles, also considering the risk aversion characterization, a new layer of characterization will be added where it is expected to find more positive self-selection between groups.

This chapter is structured as follows: Section 1 presents the relevant theory that underpins this investigation and the theoretical model. Section 2 introduces the data and identification strategy. Section 3 provides statistics and discusses the development of the model using the available data. Section 4 presents the results and robustness checks. Finally, Section 5 offers the conclusions.

Theoretical framework

Self-selection Model

Migration, as a form of human capital investment, occurs when individuals aim to maximize their returns by selecting destinations offering the most favorable opportunities. This idea, first proposed by Sjaastad (1962), suggests that migrants assess the value of opportunities at various destinations, choosing the one that maximizes their returns. Building on Sjaastad's work, Borjas (1987) introduced the self-selection framework, which argues that migration decisions are influenced by income-maximization behavior and income inequality. Suggesting that when income inequality is higher in the source country, such as between Mexico and the U.S., migrants tend to be negatively selected, meaning they are less skilled than those who remain. Borjas (1991) refined this model, showing that positive selection occurs when skilled individuals migrate to countries with higher rewards for skills, while negative selection dominates when low-skilled individuals migrate from more unequal societies.

Recent studies have emphasized the role of individual characteristics, such as risk attitudes, in migration decisions. Jaeger et al. (2010) provide direct evidence that individuals who are more willing to take risks are significantly more likely to migrate. Their research, based on data from the German Socio-Economic Panel, suggests that risk attitudes have a larger effect on migration probabilities than traditional factors such as age, sex, or education. This finding supports the idea that migration is inherently risky and that individuals with higher risk tolerance are more inclined to pursue migration as a means of improving economic opportunities.

Empirical research has tested Borjas's self-selection model, yielding mixed results. Chiquiar and Hanson (2005) challenged the negative-selection hypothesis, finding that Mexican migrants to the U.S. in the late 1990s were drawn from the middle and upper segments of Mexico's wage distribution, indicating positive or intermediate selection.

However, Fernández-Huertas (2011), using pre-emigration wage data from the National Quarterly Employment Survey (ENET by its acronym in Spanish), found evidence of negative selection among Mexican emigrants between 2000 and 2004, attributing the differences in their findings to methodological approaches. Fernández-Huertas (2011) also explored gender differences, finding that male Mexican migrants were less educated than non-migrants, while female migrants had more schooling, indicating positive selection for women. Caponi (2011) further examined education and migration, revealing a U-shaped pattern, where the least educated and most educated individuals are more likely to migrate, while those in the middle are less likely to emigrate.

Migration networks also shape the self-selection process. McKenzie et al. (2010) demonstrated that stronger migration networks increase the likelihood of negative selection by lowering migration costs for low-skilled individuals. In areas with established networks, lower-skilled migrants benefit from reduced migration costs and social support, whereas higher-skilled individuals are less reliant on such networks. Munshi (2003) supported this view, showing that networks help low-skilled Mexican migrants secure higher-paying jobs in the U.S., thus facilitating their migration.

Wage differences further highlight the self-selection process. Fernández-Huertas (2011) emphasized that Mexican emigrants earned lower wages prior to migration compared to non-migrants, supporting the negative selection hypothesis. These findings contrast with the analysis by Chiquiar and Hanson (2005), which indicated higher productivity among Mexican migrants. Fernández-Huertas (2011) attributes this discrepancy to methodological differences, particularly the undercounting of undocumented migrants. It is important to note that the use of labor force survey data to analyze migration patterns presents inherent limitations, particularly regarding migrant underrepresentation. As Fernández-Huertas (2011) argues, survey attrition can conflate international migration with other forms of household exit, leading to potential misclassification—especially for undocumented migrants. This underrepresentation may bias estimates of selection. While the present analysis seeks to mitigate such biases through disaggregation and complementary statistical methods, this caveat should be borne in mind.

A critical limitation of Borjas (1987)'s model is its assumption of homogeneity in risk aversion. In reality, individuals differ in their tolerance for risk, which can significantly influence self-selection patterns. By incorporating heterogeneity in risk attitudes, the theoretical framework provides a more nuanced understanding of migration decisions. Individuals with different risk preferences may respond differently to economic incentives and uncertainties, leading to varied selection patterns across migrant populations.

Following the same approach as Borjas et al. (2018), Chiquiar and Hanson (2005), Fernández-Huertas (2011), and others, in this chapter, an assessment of the selection bias in the Mexico and the U.S. migration dynamics is presented with the incorporation of an ex-ante risk aversion measure that will allow for a better understanding of the decision-making process. For doing the previous, the first step is to define the model that will describe the migration process in terms of income.

The two main equations that define the decision-making process are:

$$ln(w_{0i}|\overline{\lambda_i(w_{0i}, C_i^*)}) = \alpha_{0i} + r_{0i}s + \eta_{0i} \tag{1}$$

$$ln(w_{1i}|\overline{\lambda_i(w_{1i}, C_i^*)}) = \alpha_{1i} + r_{1i}s + \eta_{1i} \tag{2}$$

Where w_i is the wage in the i country; λ_i represents the level of risk aversion, i.e., the risk aversion profile, for the person i; C_i^* is the level of migration costs for each person; r_i is the rate of return of observable skills; η_i the individual specific productivity shocks resulting from the unobserved characteristics, with $\eta_i \sim N(o, \sigma_i^2)$; where $i = 1, ..., N$, 0 represent the home country ad 1 represent the host country. The distribution of observable skills in the source country in the origin country is $s = \mu_s + \varepsilon_s$, where the random variable $\varepsilon_s \sim N(0, \sigma_s^2)$.[1]

The previous equations fully describe the earnings opportunities in both the origin and destination countries. The migration decision is influenced by the individual's risk aversion profile. Specifically, when $\lambda = 0$, the individual is a risk-taker; when $\lambda = 1$, the individual is risk-averse. This ex-ante measure of risk aversion allows for the categorization of individuals and contributes to a clearer understanding of how migration determinants shape decision-making—particularly in how individuals, depending on whether they are

[1] For convenience we assume $cov(\varepsilon_0, \varepsilon_s) = cov(\varepsilon_1, \varepsilon_s) = 0$, so that the individual-specific unobserved productivity shock are uncorrelated with the observable characteristics. The correlation between ε_0 and ε_1 is equal to ρ_{01}, where rho represents the correlation between two variables.

risk-takers or risk-averse, interpret and respond to their contextual environment. Therefore, the migration decision can be expressed through the comparison of earnings levels using the following index function:

$$\begin{aligned} I &= log(\tfrac{w_{1i}}{w_{0i}+Ci^*}) \\ &\approx [(\alpha_{1i}-\alpha_{0i})+(r_{1i}-r_{0i})\mu_{si}-\pi^*]+[(r_{1i}\varepsilon_{si}+\varepsilon_{1i})-(r_{0i}\varepsilon_{0i}+\varepsilon_{0i})] \\ &= \Delta\mu+(v_{1i}-v_{0i})>0 \Rightarrow \quad \textbf{migration} \quad \textbf{occurs} \end{aligned} \tag{3}$$

Where $\pi^* = C^*/w_{0i}$ represent the time-equivalent migration costs; $\Delta\mu = (\alpha_{1i}-\alpha_{0i}) + (r_{1i}-r_{0i})\mu_{si} - \pi^*$ is the cross difference in earnings net the time-equivalent migration costs fro an individual with average observed and unobserved skills; and $(v_{1i}-v_{0i})$, where $v_{ji} = (r_{ji}\varepsilon_s + \varepsilon_{ji)}$, where $j = \{0 : home, 1 : host\}$, is the difference in earnings due to individual deviations from average characteristics.

Given the risk aversion profile defined by the λ risk aversion identifier within the group and their respective distributions, it is possible to define comparison groups according to a similar set of characteristics for the decision-making process. In that sense, it is possible to say that the decision-making process has been refined due to the incorporation of a risk measure that varies from individual to individual and from group to group; therefore, there are different types of migrants and non-migrants that consider the context and their characteristics and how this impact in these has an effect in the migration decision.

The last allows U.S. to understand the relationship between risk aversion, migration costs, and the characteristics of individuals. In the sense that intuitively a person with a better context will face less non-monetary costs to consider in the decision to migrate, i.e., a better level of skills, less credit constraints, assets in the home country, a shared responsibility in the origin country household, better physical capabilities (lower probability of getting hurt or sick during the migration or overseas process, etc.) for migration, should be able to face better the cost associated with the decision of migrate, and therefore be less risk-averse to initiate the migration process (Sjaastad, 1962). Adding earnings to the process will enhance the prediction about the migration decision, that is, a person with a better context will be less risk-averse and with higher earnings will face the migration process more easily or even without concerns. The previous works the same for legal and illegal migration.

Figure 1: Model RA vs RT

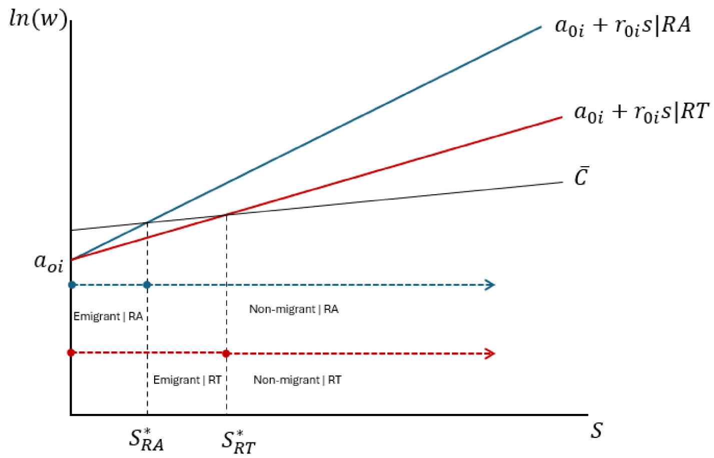


Figure 1 illustrates the migration decision-making model by distinguishing between risk-averse and risk-taker individuals. The model assumes that $r_{0i}|RA > r_{0i}|RT$, indicating that individuals with identical observable characteristics but differing risk profiles will perceive and react to wage structures differently. The graph incorporates a constant migration cost structure over time, allowing us to isolate how individuals internalize these costs based on their expectations, contextual constraints, and particularly their degree of risk aversion.

Risk-averse individuals, valuing stability and certainty, assign a higher implicit value to their skills in the home country. As a result, their expected return from staying is significantly higher, making migration less attractive unless the benefits are substantial. This leads to a higher threshold of skills (S^{RA}) required for migration. In contrast, risk-takers are more willing to migrate even when expected returns are lower, given their lower sensitivity to uncertainty. Accordingly, their migration threshold (S^{RT}) lies further to the right, meaning they are more likely to migrate even with relatively higher skills but lower perceived returns.

These dynamics shed light on how migration reshapes the composition of the labor force in Mexico. As domestic labor market conditions shift—such as wage stagnation or increased competition for jobs—migration becomes a more attractive alternative. For instance, new entrants into the labor force may depress wages at certain skill levels, further incentivizing migration. This makes migration not only viable for risk-takers but increasingly compelling for risk-averse individuals as well.

Incorporating a measure of individual risk aversion into the model provides a richer understanding of the evolving migration landscape. It allows for a more nuanced view of the decision-making process and how different types of individuals respond to structural changes in both the home and destination countries.

Borjas identified and established a negative selection bias within Mexico-U.S. migration, indicating that individuals from the lower end of the skills distribution are more likely to migrate to the U.S. However, migration is fundamentally a human capital investment decision, and following Sjaastad's approach, attitudes toward risk are crucial in shaping this process. In this context, an ex-ante measure of risk aversion is essential for understanding the differences between individual profiles in the sending country, as well as the main reasons and characteristics influencing their decision to migrate.

Risk aversion profiles deepen the analysis of individuals' decision-making processes and contexts. Risk-tolerant individuals are more likely to migrate, even with lower income expectations, due to their personal characteristics and circumstances in the sending country. Conversely, risk-averse individuals typically have higher income expectations, shaped by their self-assessment of their skills and perceived value.

The introduction of an ex-ante classification of profiles into the model creates a two-group framework: one for risk-averse individuals and another for risk-takers. This distinction significantly affects the empirical analysis of the model. Theoretically, it modifies how equations are formulated, as shown in Figure 1. These equations account for individuals' willingness to accept risk in combination with their income expectations, the anticipated return on their skills, and other demographic characteristics.

Empirical evidence reveals that a larger proportion of risk-takers choose to migrate compared to risk-averse individuals. Analyzing the distribution of migrants based on their risk profiles highlights this trend. Additionally, demographic characteristics suggest that risk-averse individuals often face more competitive environments in both Mexico and the U.S.. This, combined with the inherent risks of migration, associated costs, and income expectations, shapes their decision-making process and contributes to the observed selection bias. Evidence supports a clearer positive selection for risk-takers than for risk-averse individuals, underscoring the importance of risk attitudes in migration dynamics.

Risk aversion

The decision-making process in the context of migration and investment under uncertainty can be viewed as a two-step procedure. First, an individual efficiently chooses among all available options without regard to personal preferences and then applies those preferences to select the option that best suits their needs (Hanoch & Levy, 1969). This framework links the concept of riskiness to migration decisions, where individuals must consider both external determinants and their own risk preferences. Consequently, understanding risk aversion is essential for explaining such decisions.

Risk aversion plays a critical role in decision-making under uncertainty, particularly in fields such as migration and investment. Traditional utility-based approaches to risk aversion have been criticized for their limitations in capturing the complexities of human behavior. Thomas (2016) offers a more realistic approach by using dimensional analysis to understand how people make decisions in risky scenarios. This method challenges the idea that risk aversion can be understood solely through utility models, suggesting instead that risk preferences are more nuanced and context-dependent. In exploring how household wealth affects risk aversion, Brunnermeier and Nagel (2008) find that fluctuations in wealth have little impact on individuals' risk attitudes, contrary to predictions by habit-formation models. Their research shows that inertia—rather than changes in wealth—plays a greater role in determining how people allocate assets, further complicating our understanding of risk aversion in dynamic financial contexts.

Levy (1992) and later Leshno and Levy (2002) contributed significantly to the field by introducing the concept of Almost Stochastic Dominance (ASD), which addresses situations where traditional stochastic dominance rules are insufficient. ASD allows decision-makers to rank alternatives based on the preferences of the majority, making it particularly useful in finance and investment, where utility functions may vary across individuals (Leshno & Levy, 2002). This concept is valuable in decision-making under risk, especially in diverse populations where risk preferences differ.

Building on these ideas, Davidson and Duclos (2000, 2013) apply stochastic dominance to broader social issues, such as poverty and inequality. They develop robust statistical methods for comparing income distributions and measuring welfare improvements. These techniques help decision makers assess not only financial risks but also the societal impacts of economic policies. Thistle (2008) further refines the understanding of risk aversion by introducing models that incorporate negative moments and stochastic dominance principles. His work demonstrates how economic agents can make optimal decisions under uncertainty, providing a framework for evaluating choices in both migration and financial contexts.

The notion of risk aversion, as defined by Thomas (2016), is the feeling that guides a person facing uncertain outcomes—whether related to money, status, happiness, or other important life aspects. By generating a relative risk aversion measure that accounts for individual characteristics, it becomes possible to recover not only the monetary costs associated with migration but also non-monetary costs. This approach provides a more precise measure of both the costs and returns of migration, factoring in individuals' perceptions of risk and how they internalize their surrounding context (Dustmann, Fasani, et al., 2017).

To calculate this measure, a Taylor series expansion is typically used to estimate the individual's risk aversion based on their starting wealth. This method has the advantage of not requiring a specific utility function, and it accommodates changes in risk aversion during pairwise comparisons of alternatives. This approach ensures a more flexible and comprehensive assessment of how individuals evaluate risky decisions in uncertain environments. There are good reasons for considering the risk aversion to differ between individual profiles, more if we consider the heterogeneous origin of migrants in Mexico, not only because of geography, but also because of differences in the level of development and capabilities.

Let there be a lottery that offers a prize of $w_{i,1}$, that is, the wealth the agent has in the foreign country, and $w_{i,0}$ that is the initial wealth of the agent in the foreign country, where i denotes the agent. This means that the agent could have the new wealth only if she decides to migrate, that is, the wealth can only be $w_{i,1}$ or $w_{i,0}$. The previous lottery has the probability p of occurrence, therefore, the probability of non-occurrence is $1 - p$. that is, the expected utility of the lotteries is[2]:

$$E[w_{i,1}] = p \cdot w_{1i} + (1 - p) \cdot 0 = pw_{1i} \tag{4}$$

The agent has to define the threshold to identify the limit she is willing to spend or pay to migrate to another country. For this purpose, a maximum price to pay for migration is defined, $c_i = pw_{1i}$, which is also equal to $E[w_{1i}]$, the risk neutral position, that is, the risk aversion is equal to zero. With the previous, we can expect that a different maximum amount to pay will also indicate the level of risk aversion (λ), given the level of wealth or wage she has in the current country (country of origin at the moment).

Once the ticket of migration is paid, the current wealth decreases by the amount paid, leading to a new level of utility $U(w_{i,0} - c_i)$, in the case where the migration occurs, then she also wins the new wage $w_{i,1}$, if not, then she only reduces his current wage, the previous transforms the expected utility as follows:

$$E[U] = p \cdot u(w_{0i} + w_{1i} - c_i) + (1 - p) \cdot u(w_{0i} - c_i) \tag{5}$$

[2]In this analysis, monthly labor income reported in the ENOE is used as a proxy for individual wealth. While ideal wealth measures would include assets and savings, such data is not consistently available in ENOE. Given the structure of the Mexican labor market and the relatively low levels of asset accumulation among the working population, monthly income serves as a reasonable approximation of financial capacity. This proxy aligns with prior migration and risk-aversion studies that rely on income to reflect individuals' ability to absorb migration costs and make intertemporal decisions under uncertainty (Borjas, 1987; Chiquiar & Hanson, 2005; Jaeger et al., 2010).

where $w_{1i} - c_i < w_{0i}$ and $c_i < w_{1i}$. With this it is possible to expand the two terms on the right side with a Taylor expansion in order to obtain the risk aversion measure.[3]

$$-\frac{u''(w)}{u'(w)} \leq \frac{2(pw_{1i} - c_i)}{pw_{1i}^2 - 2pw_{1i}c_i + c_i^2} \tag{6}$$

Now, the individual has a way to compare if she has at least no loss without regard if she decides to migrate or not. Taking the previous result, we can multiply equation (6) by the initial wealth (the wage the agent has at the beginning a in the origin country); it is possible to obtain the relative measure of risk aversion and introduce a richer way to characterize the way the agent internalizes his context, i.e.:

$$\lambda_i \leq \frac{2w_{0i}(pw_{1i} - c_i)}{pw_{1i}^2 - 2pw_{1i}c_i + c_i^2} \tag{7}$$

With this risk aversion equation, we can identify that two key levels of risk aversion that help us to understand the way agent behaves and takes her decision: the maximum price to pay given her wealth and characteristics and the break even point that set the threshold. For the first level, we have to identify when the inequality change direction, this will be at the point where the price is the maximum that can be absorbed in order to migrate, meaning that we have $\lambda(max|c_i, w_i)$ and from this expression we can identify the also the maximum price to pay $c_{i,max}$.[4]

Now that we know the maximum price to pay, we can set a break-even point that implies looking at the case where the inequality in (6) is an equality.

$$\lambda_{i,BE} = \frac{2w_{0i}(pw_{1i} - c_{i,max})}{pw_{1i}^2 - 2pw_{1i}c_{i,max} + c_{i,max}^2} = \frac{2w_{0i}/c_{i,max}(pw_{1i}/c_{i,max} - 1)}{p(w_{1i}/c_{i,max})^2 - 2pw_{1i}/c_{i,max} + 1} \tag{8}$$

To empirically implement this model, I use data from the ENOE (2007–2017) to recover wages for both migrants and non-migrants, construct migration probabilities by survey wave, and merge these with exogenous estimates of migration costs. The risk aversion

[3]The advantage of using a Taylor expansion is that we can generate a risk aversion measure independently of the precise utility function.

[4]It is necessary to have in mind that the risk aversion is a function of c_i and it is decreasing as c_i if, and only if, c_i is in the range $0 < c_i < c_0(1 + \sqrt{(1 - p/p)^{\frac{1}{2}}})$

measure derived in equation (7) is then applied at the individual level, capturing how each person weighs expected income gains against the costs and uncertainty of migration. Specifically, the measure uses observed hourly wages in the origin and destination contexts (w_{0i}, w_{1i}), the probability of migrating (p), and the estimated migration cost (c_i), allowing for the calculation of a relative risk aversion index λ_i.

To interpret this metric, I calculate a break-even threshold based on the maximum migration cost an individual can absorb, $c_{i,\max}$, and derive a reference risk aversion level $\lambda_{i,\mathrm{BE}}$ at which the agent is indifferent between migrating or staying. Individuals whose estimated λ_i falls below this break-even value are classified as risk-takers, while those with a higher λ_i are deemed risk-averse. This classification introduces behavioral heterogeneity into the migration model, enabling a richer understanding of self-selection and decision-making processes.

Furthermore, individuals are grouped into clusters based on observable characteristics—such as income level, education, and region—to assess how structural conditions shape both risk preferences and migration behavior. These groupings enable not only the comparison of migration probabilities but also the application of stochastic dominance techniques to assess how differences in context and risk aversion influence economic mobility across populations.

Risk aversion identification

Equation (7) provides the foundation for estimating individual-level risk aversion by incorporating wages in both the origin and destination contexts, the probability of migration, and migration costs. In this analysis, monthly labor income is used as a proxy for wealth, as it reflects individuals' immediate financial capacity and their ability to absorb migration-related risks. While comprehensive wealth data is unavailable in ENOE, monthly income serves as a practical and commonly accepted substitute, particularly in low-asset contexts where income drives most financial decision-making.

To operationalize the measure, an index of risk aversion is computed for each individual using average migration costs observed during a specific period. Additionally, a reference threshold is established using the maximum migration cost reported annually, drawn from external data provided by the Mexican Migration Project. This threshold represents the highest cost that can be absorbed given the wage and probability parameters in the model.

Individuals whose estimated risk aversion level exceeds this threshold are classified as risk-averse, while those below the threshold are considered risk-takers.

This methodology enables the classification of both migrants and non-migrants according to their risk profiles. By combining observed income, modeled costs, and migration probabilities, the resulting risk aversion index provides a consistent way to identify heterogeneous decision-making patterns within the population. This classification is subsequently used to examine how risk preferences interact with migration decisions and contextual constraints across different groups.

Stochastic Dominance

Stochastic dominance helps us to understand how one option is preferred over another option given the maximization process over lotteries without knowing the specific characteristics for a particular utility function. Borjas et al. (2018) presented an approach that shows how the first stochastic dominance holds for the self-selection model. This approach allows us to compare groups of migrants and non-migrants through their distributions to characterize the selection bias following these two notions:

Having two generic distributions that are bounded to a common support set [a,b] with $F(a) = G(a) = 0$ and $F(b) = G(b) = 1$, then [5]:

- When a lottery F first-order stochastically dominates G, the decision maker prefers F to G regardless of what u is, as long as it is weakly increasing.
- When a lottery F second order stochastically dominates G, the decision maker prefers F to G as long as she is risk-averse and u is weakly increasing.

Data

In order to test the model the main source for the data is the ENOE, following the exercise done by Fernández-Huertas (2011) with the National Urban Employment Survey (ENEU, for its Spanish acronym) and the Employment National Survey (ENE, for its Spanish

[5] Formal definitions of FOSD and SOSD are available at the annex

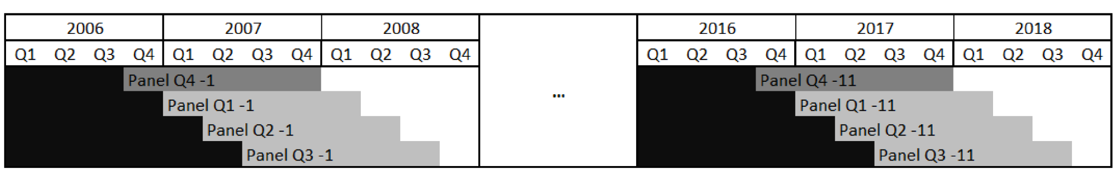
acronym), I will use the consolidated project the National Occupation and Employment Survey (ENOE, for its Spanish acronym), as it has the advantages pointed out by Fernandez Huertas; this will be explained in the identification strategy. The secondary data for this exercise is the panel of the Mexican Migration Project that for this exercise provides the cost of migration that is needed for the calculation of the risk aversion measure.

National Occupation and Employment Survey.

The ENOE, for its Spanish acronym, is a nationally representative survey that collects comprehensive data on employment and labor force dynamics in Mexico. It allows assessing the participation of individuals in the labor force, distinguishing between those who are employed, unemployed, and those who are not in the labor force. It classifies individuals based on their employment status, such as wage and salary workers, self-employed individuals, and unpaid family workers; collects data on the specific occupations and industries in which individuals work,and demographic data (such as age, gender, education, and household composition, allowing for a detailed analysis of labor market dynamics across different population groups).

One of the key characteristics of this survey is that it can be constructed as a rotative panel that involves tracking and re-surveying the same individuals and households over multiple quarters or waves (5 in total). This process creates a longitudinal dataset that allows to study changes in employment, income, and other labor market variables for the same individuals over time. The previous facilitates the study of the effects of economic events, policy changes, and social factors on the labor market outcomes of specific individuals and groups. In Figure 2 is shown how the panels are constructed.

Figure 2: Data structure



Source: ENOE, INEGI.

Mexican Migration Project

The Mexican Migration Project (MMP) is a collaborative research project based at Princeton University and the University of Guadalajara. It is an extensive research initiative that collects and analyzes data related to Mexican migration to the United States. Specifically, it focuses on understanding the patterns, causes, and consequences of Mexican migration. It is a longitudinal data survey, which allows one to study the dynamics of migration, including the decision-making processes, migration histories, and the impacts on both sending and receiving communities. One of the central components of the MMP is the collection of data from Mexican migrants in the United States, including demographics, economic conditions, education levels, and migration histories of household members. In addition, information about legal status, employment, remittances, and family ties on both sides of the border.

This dataset provides information on migration costs paid across different waves, a crucial variable for developing the risk aversion measure used in this research. By analyzing migration costs, it becomes possible to assess individual risk profiles. Additionally, the maximum migration cost—which serves as the break-even point distinguishing risk-averse individuals from risk-takers—is derived from this dataset by estimating the highest cost paid per year. These two key variables, migration cost and break-even point, are provided by the Mexican Migration Project (MMP) for this research. However, a key limitation of the panel is its level of representativeness. Despite this limitation, the dataset remains a valuable resource for understanding the financial constraints and risk attitudes of migrants.

The MMP Database (MMP134) is currently one of the most concise and vast data sets of its kind in existence. It comprises 134 communities with 21,522 households surveyed in Mexico and 957 households surveyed in the United States. Individual level data on 71,448 males and 72,805 females, for a total of 144,258 persons. It contains information about 7,398 household heads with migration experience to the U.S.. The life history file has a total of 1,082,322 of person-years for analysis.

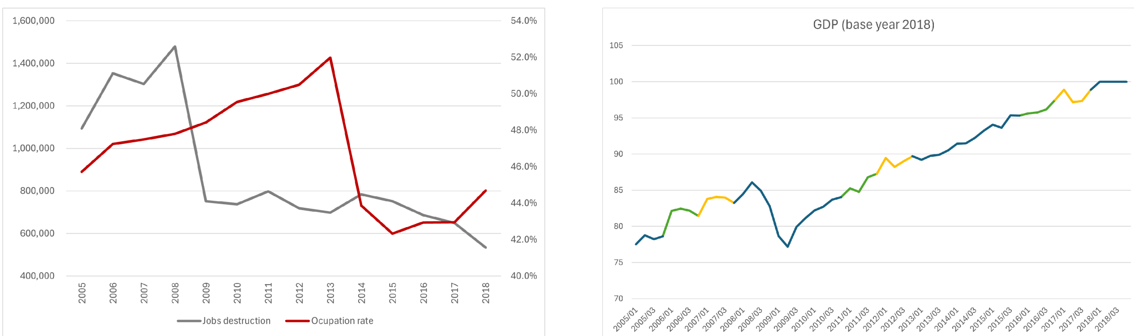
Data limitations.

Although the ENOE is one of the most reliable datasets for analyzing socioeconomic dynamics in the Mexican context, it has limitations when it comes to studying migration dynamics, as it only captures migration flows rather than long-term trends. Due to this limitation, it is possible that the ENOE data in our analysis primarily reflects individuals' responses to short-term shocks that influenced their decision to migrate. This phenomenon, known as the Ashenfelter Dip bias [6], could introduce significant distortions into our analysis.

The factors influencing individuals' decisions are numerous. However, by analyzing migration as an economic phenomenon related to the labor market, job destruction and occupation rate emerge as two key indicators for understanding the economic context in which decisions are made. Alongside GDP, used as a proxy for overall economic activity in the country, these indicators make it possible to rule out the presence of the Ashenfelter Dip bias.

Figure 3: Job destruction, occupation rate & GDP

(a) **(b)**



Source: ENOE & National Accounts, INEGI.

As can be observed in Figure 3a and 3b, the behavior of job destruction and the occupation rate tend to follow opposite trends, particularly during the years under study. Considering that the aim to analyze short-term economic shocks, we are interested in examining the years immediately preceding those under study: 2006 for 2007, 2011 for 2012, and 2016 for 2017. In all three cases, we observe a decrease in job destruction and an increase in both the occupation rate and GDP. This suggests an active economic environment where job openings are being filled while the number of jobs lost is declining.

[6] This bias highlights how individuals who self-select into a program or decision often do so in response to adverse events or declining outcomes, such as a sudden drop in income or employment. This creates a bias because these individuals' pre-program characteristics are not representative of the general population. Their decision to participate or to choose one outcome is influenced by their recent negative experiences, making it difficult to isolate the program's or expectations true effect from their natural recovery or regression to the mean.

Additionally, the analysis faces important sampling constraints, particularly related to the representation of migrants in the ENOE. Given the comparatively small number of observations for migrants—especially when disaggregated by year and individual characteristics such as risk aversion—the statistical power of certain tests may be limited. This may affect the detection of subtle differences between groups, especially in the tails of the income distribution. Therefore, while standard tests of significance are employed throughout the analysis, complementary strategies—such as bootstrap estimation—are also used to support the interpretation of potential self-selection patterns. These methodological choices aim to provide a more robust understanding of the migration-income relationship despite the underlying limitations of the dataset.

Migrants' identification strategy

The first step is to define how individuals are identified as migrants. A migrant is a person who is surveyed at least once during the first quarter of a panel and subsequently disappears in the next quarter or one of the following quarters. This approach enables the construction of a panel for each period during which new participants are added to the survey. Conversely, a non-migrant is someone who remains in the panel for all five quarters, regardless of the quarter in which they were initially surveyed. Due to the structure of the data, it is possible to create up to four panels each year.

This identification strategy ensures the inclusion of a sufficiently large cohort of migrants and non-migrants to analyze potential selection bias. Additionally, for each panel, the head of the household is identified and selected. The panel is then constructed based on this selection, with the goal of determining the exact moment when the individual exits the panel—indicating the point at which they migrate.

Selection in pre-migration earnings

The ENOE survey has been collecting data since 2005 without interruption. Therefore, it is one of the most reliable data sets in Mexico for analyzing different social and economic dynamics, given the questionnaires it uses and the consolidation of the survey over time. One key advantage of using ENOE data is its ability to clearly identify migrants, enabling effective comparisons between migrants and non-migrants. Migrants can be tracked in the data prior to their decision to migrate, allowing for a direct comparison of the two groups in the period leading up to migration. This approach ensures that the earnings being compared are those of each individual during the period before they decide to migrate. As a result, it is possible to compare individuals simultaneously having an observable counterfactual group.

This analysis focuses on examining selection bias. The years 2007, 2012, and 2017 were selected for this purpose, representing an initial point before the 2007 economic crisis, a midpoint to capture potential changes, and an endpoint that reflects economic composition shifts after they have stabilized. For each of these years, four quarterly panels will be used, as specified in the ENOE documentation.

Descriptive statistics

This research utilizes the socioeconomic survey from the ENOE to analyze selection bias. The survey includes a specific question that identifies individuals who leave the dataset due to emigration, along with details about their destination. For the purposes of this study, the analysis focuses exclusively on household heads, providing a consistent basis for the descriptive statistics.

Table 1: Descriptive statistics for men and women by migration status (RA and RT)

	Men				Women			
Descriptive Statistics	**RA Non-mig**	**RA Mig**	**RT Non-mig**	**RT Mig**	**RA Non-mig**	**RA Mig**	**RT Non-mig**	**RT Mig**
Obs	2207020	2016	2413625	1632	787863	163	853136	137
%	99.91	0.09	99.93	0.07	99.98	0.02	99.98	0.02
Age								
Mean	47.3	40.1	47.5	40.0	52.5	49.6	52.5	51.0
Median	46	39	46	39	51	48	52	50
Rural	36.93	67.34	32.19	70.04	31.21	42.34	27.05	39.88
Schooling								
Mean	9.3	9.3	8.3	8.1	8.9	10.2	8.3	8.1
Median	9	9	9	8	9	9	9	9
Labor force participation	58.75	94.45	55.31	100	58.79	82.77	62.58	100
Wage earners	45.19	86.84	40.58	100	45.01	78.59	42.33	100
Government support	3.9	2.08	4.66	2.39	3.87	4.37	6.13	2.19
Monthly income (Mean in pesos)	5526.42	6494.10	444.47	521.58	4672.99	7535.67	444.20	724.62

Source: ENOE, INEGI

Table I presents general statistics, highlighting the sample sizes for each group. It is evident that the risk-averse group is significantly larger than the risk-taker group. This discrepancy poses a limitation when the data is further disaggregated by gender and year. To address this, a secondary analysis is provided in the annex, where gender characterization is replaced with rural and urban classifications. This additional exercise underscores the importance of context in migration decisions and demonstrates that rural origin remains a significant determinant of income and risk aversion profile characterization, as will be discussed in a later section.

When examining the backgrounds of individuals, it is apparent that most migrants originate from rural areas, with an average of 68% of migrant men and 41% of migrant women coming from rural environments. This finding highlights the critical role of context in shaping access to development resources. Regarding education, non-migrants tend to have higher levels of schooling on average, except for risk-averse women, where the relationship reverses. A similar dynamic is observed for mean monthly income.

An important finding is that migrants tend to receive less government support than non-migrants, likely due to limited access to social programs. This disparity is especially pronounced among migrants from rural areas, where the lack of access to such resources significantly impacts their profiles and opportunities. Another important finding is in the relationship that monthly income has between the groups, as migrants groups have a higher income than non-migrants. in the case of risk-averse men migrants they report an average 17.1% of more income, meanwhile for the same groups of women there is a 61.2% more income. in the case of risk-takers the difference in monthly for men's is on average 17.3% and for women's is 63%. In both all the cases, as mentioned above, the migrant groups has higher monthly income on average, and given the the dynamics of schooling, there seems to be a higher level of productivity in migrants groups than in non-migrants groups, these results support the idea of positive selection; nonetheless, it is necessary to consider that we are aggregating the three periods for this and more precise tools are needed to conclude the sort of selection bias.

Table 2 presents data on urban migration, showing that migrant groups exhibit higher rates of urban migration compared to non-migrants. This is largely because migrants often emigrate to the U.S., but this trend may also be influenced by individual and idiosyncratic characteristics.

Table 2: Urban migration percentage by quarter within the panel

Year	Q	Non-mig RA	Non-mig RT	Mig RA	Mig RT
2007	2	15.8%	14.3%	5.0%	5.0%
	3	16.0%	12.7%	5.7%	5.7%
	4	16.0%	12.1%	8.6%	8.6%
	5	16.0%	11.4%	5.7%	5.7%
2012	2	16.7%	13.8%	8.1%	4.1%
	3	16.1%	11.2%	8.2%	8.2%
	4	16.1%	7.7%	14.0%	1.3%
	5	15.7%	4.9%	6.7%	3.4%
2017	2	17.3%	13.6%	5.3%	1.4%
	3	17.4%	12.3%	2.6%	6.3%
	4	17.7%	11.6%	7.5%	4.0%
	5	17.5%	11.2%	4.3%	2.7%

Source: ENOE, INEGI

Note: the first quarter of each panel was omitted as it was only possible to track urban migration since the second quarter.

Another important phenomenon and relationship to observe is the employment and unemployment rate within the migrant cohorts over time, as the performance in the labor market can categorically influence the decision of migration. A sudden and negative shock can be the pivotal point to define the migration decision; in this sense, by looking at the employment and unemployment rates for migrants it is possible to see if at some point in time there was a negative shock. In Table 3 we can see both rates. In terms of employment, the rate tends to be very similar over time, with only one significant negative change in Q3 of 2017; nevertheless, the rate recovered a regular path for the last two quarters. Now when looking to unemployment, a similar behavior is observed and the magnitude of the rate is high but stable.

Decomposing the average income by year, in Table 4, it is interesting that for 2007 and 2017 the income of migrants is higher than the income for non-migrants for the last three age groups (40 to 49, 50 to 59, and 60 +), and in 2012 only for one of those three groups,

Table 3: Migrant employment and unemployment by quartile (2007, 2012, and 2017)

Year	Employment	Unemployment
2007		
Q2	75.3%	24.7%
Q3	72.0%	28.0%
Q4	74.3%	25.7%
Q5	75.4%	24.6%
Avg	74.3%	25.7%
2012		
Q2	73.3%	26.7%
Q3	76.7%	23.3%
Q4	78.3%	21.7%
Q5	92.6%	7.4%
Avg	80.2%	19.8%
2017		
Q2	80.9%	19.1%
Q3	64.4%	35.6%
Q4	79.5%	20.5%
Q5	79.4%	20.6%
Avg	76.0%	24.0%

Source: ENOE, INEGI

the one for 50 to 59. In the case of the first three groups (14 to 19, 20 to 29 and 30 to 39) the average income is higher for the three years. This is relevant as the average age for each group (RA and RT men and women migrants and non-migrants) analyzed in this research is over 40 years. This is something to keep in mind when analyzing the results as this could be a signal of how there could be intermediate self-selection in terms of skills given the Mexican labor market.

In contrast with the average monthly income, the relationship between migrant and non-migrants groups the average schooling, in Table 5, of the first three age groups of migrants is higher than the one for non-migrants, and following the same dynamic as in the average income the last three groups have the inverse relationship, having a lower level of schooling in the last three groups of migrants than the groups of non-migrants. Again, this could be an indicative of changes in the composition of the migrants and non-migrants groups that could lead to a modification in the self-selection patterns between groups and over time.

Table 4: Average monthly income by age group (MXN pesos) for Non-migrants and Migrants (2007, 2012, 2017)

Age Group	Non-migrants (MXN pesos)			Migrants (MXN pesos)		
	2007	**2012**	**2017**	**2007**	**2012**	**2017**
14 to 19	2332.9	2676.6	3107.7	2363.3	0.0	0.0
20 to 29	4080.6	4227.1	4984.3	4007.0	3463.9	4825.3
30 to 39	4925.5	4713.8	5368.5	4797.4	4344.7	5273.9
40 to 49	4940.0	4541.7	4885.7	5443.0	4159.5	5525.0
50 to 59	3886.8	3667.7	3991.2	3981.9	4001.4	4215.6
60+	1283.2	1225.9	1406.5	1417.9	1109.5	1569.7

Source: ENOE, INEGI

Table 5: Average schooling by age group for Non-migrants and Migrants (2007, 2012, 2017)

	Non-migrants						Migrants					
Age Group	**14 to 19**	**20 to 29**	**30 to 39**	**40 to 49**	**50 to 59**	**60+**	**14 to 19**	**20 to 29**	**30 to 39**	**40 to 49**	**50 to 59**	**60+**
2007	9.4	9.9	9.8	9.6	8.1	5.1	10.2	10.2	9.9	9.6	8.5	5.6
2012	9.3	10.5	10.1	9.9	9.0	5.9	12.0	10.6	9.7	9.6	10.1	5.7
2017	9.8	10.9	10.8	10.2	9.6	6.7	11.0	11.0	10.8	10.3	9.1	6.8

Source: ENOE, INEGI

Also, by looking at the average and median age of migrants by gender, we can observe how the decision of migrate is delayed or at least considered at different stages of their labor life, as in the case for women in the three years they do it at an older stage than men. The difference in schooling levels is also clear, as women tend to have a higher level of instruction than men's, and in the three years the average income per hour is lower for women, showing a clear disparity in wages, in this case not only for migrants and non-migrants. By looking at the structure of wages between migrants and non-migrants, we can expect a lower level for migrants; nonetheless, for women in 2007 the previous does not happen, the same for the schooling level. These behaviors give us an indication of the relationships and possible differences in self-selection biases.

Table 6 shows that for male non-migrants who are risk-takers, the majority are concentrated in the 60+ age group, while for risk-averse individuals, the concentration is in the 30–49 age group. For women non-migrants, the age group distribution mirrors that of men, with similar concentrations in the respective risk profiles. Among male migrants, the age distribution aligns with that of their non-migrant counterparts, and the same pattern is

Table 6: RT (Risk taker) and RA (Risk averse) percentages for Men and Women by migration status, 2007–2012-2017.

		Men				Women			
Year	**Age**	Non-mig RT	Non-mig RA	Mig RT	Mig RA	Non-mig RT	Non-mig RA	Mig RT	Mig RA
	14 to 19	0.4%	0.4%	0.3%	0.5%	0.5%	0.4%	0.0%	0.0%
	20 to 29	5.6%	11.8%	4.2%	11.5%	5.5%	10.4%	5.7%	4.7%
	30 to 39	12.5%	27.3%	13.3%	28.2%	12.2%	24.4%	9.1%	25.8%
2007	40 to 49	17.8%	27.8%	19.1%	28.5%	17.8%	26.9%	34.4%	32.1%
	50 to 59	19.6%	18.8%	19.0%	19.8%	19.7%	19.3%	10.9%	23.5%
	60+	42.0%	13.9%	41.8%	11.5%	42.4%	18.5%	40.0%	14.0%
	N/A	2.1%	0.0%	2.3%	0.0%	2.0%	0.1%	0.0%	0.0%
	14 to 19	0.3%	0.4%	0.6%	0.0%	0.4%	0.4%	0.0%	0.0%
	20 to 29	5.5%	11.4%	8.9%	24.0%	5.7%	9.0%	0.0%	0.8%
	30 to 39	12.8%	24.4%	8.8%	23.4%	12.7%	20.5%	9.4%	63.5%
2012	40 to 49	18.6%	26.8%	20.9%	18.9%	18.6%	25.1%	11.3%	4.6%
	50 to 59	21.2%	20.2%	18.0%	19.7%	21.1%	21.2%	8.8%	27.2%
	60+	40.0%	16.7%	42.2%	14.0%	40.0%	23.8%	70.5%	3.9%
	N/A	1.7%	0.0%	0.6%	0.0%	1.7%	0.1%	0.0%	0.0%
	14 to 19	0.2%	0.3%	0.1%	0.0%	0.2%	0.3%	0.0%	0.0%
	20 to 29	4.9%	10.8%	4.5%	12.8%	5.0%	9.3%	1.8%	20.4%
	30 to 39	11.9%	23.2%	15.7%	22.7%	11.8%	20.4%	15.9%	12.0%
2017	40 to 49	18.2%	27.2%	19.0%	30.3%	18.3%	26.0%	24.8%	40.0%
	50 to 59	20.6%	21.4%	17.8%	20.6%	20.6%	21.5%	36.4%	12.1%
	60+	42.6%	17.0%	42.1%	13.6%	42.6%	22.4%	21.0%	15.5%
	N/A	1.6%	0.1%	0.6%	0.1%	1.6%	0.1%	0.0%	0.0%

Source: ENOE, INEGI

observed for women migrants. This composition remains consistent across the other two years analyzed, 2012 and 2017.

One effective way to analyze migration patterns is through Kernel density estimation, a non-parametric technique that does not impose a specific functional form on the data. This flexibility is especially important in migration research, where key variables such as earnings or educational attainment often deviate from standard parametric distributions like the normal distribution. Kernel methods allow for a more accurate and detailed representation of the underlying data, capturing subtle distributional differences that might be missed by parametric approaches. Their adaptability also enables the simultaneous examination of multiple dimensions—such as demographic traits, earnings, and risk aversion—within a unified analytical framework, making them particularly well-suited for studying the complex behavioral and economic dynamics of migration.

The methodological approach for testing self-selection builds on prior work by Borjas et al. (2018), Chiquiar and Hanson (2005), and Fernández-Huertas (2011), with Kernel density estimation serving as the primary analytical tool. A key innovation in this study is the inclusion of an ex-ante risk aversion measure as a central control variable in the analysis. In addition to standard kernel density plots, kernel difference graphs are used to visually represent the distributional differences between migrants and non-migrants (computed as migrants minus non-migrants). The analytical structure proceeds in three stages: first, the presence of selection bias is tested by comparing the Kernel density estimates across groups; second, kernel differences are examined to assess the direction and magnitude of that bias; and third, the findings are validated using the risk aversion classification developed in the previous section, focusing on three reference years—2007, 2012, and 2017.

Results

The composition of the distribution between migrants and non-migrants, along with the analysis of both groups, provides valuable insights into their potential interactions in the labor market and the broader economy. Given the implications for economic policy and key productive sectors, it is crucial to re-assess the composition and characteristics of migration.

Additionally, the constantly evolving migratory policies and contexts in the U.S. and Latin America can influence how individuals make migration decisions, potentially altering the characteristics of migrant groups. This analysis can help improve the design and implementation of migration policies by offering a clearer understanding of these dynamics.

Income and skills

To evaluate migrant selection, the first step is to analyze the relationship between income, individual characteristics, and risk aversion. Table 7 presents the results of a regression [7] on the log of monthly income, providing insights into the determinants of income and the key characteristics influencing income-related decisions. The first column displays results for non-migrants, while the second column shows results for migrants. It is important to note that the income variable reflects pre-migration earnings, meaning the data captures individuals before they migrate.

Overall, the results are significant for all variables, with only a few showing a change in the direction of their effects. This outcome is expected, as individuals being compared with peers from the same location typically share a similar context. However, individual characteristics, preferences, and perceptions of their environment are likely to drive the observed differences and influence the decision to migrate.

Having a family has an opposite effect on migrants and non-migrants, aligning with the idea that one of the main motivations for migration is the expectation of a higher income to support one's family. This is consistent with the results for marital status: individuals who are separated or divorced show a positive effect, while for other marital statuses, the coefficients are negative across both groups. Coming from a rural environment has

[7] The dependent variable is the log of the monthly income, and the independent variables are: having a family, that is, having at least a three-person household (two adults and at least one child); being married; live in a rural location; years of schooling declared: age cohorts (14 to 19, 20 to 29, ..., 60+; living in one of the 10 states with the highest rate emigration to the U.S., according to the Mexican Census of 2010 (Jalisco, Michoacán de Ocampo, Guanajuato, Veracruz de Ignacio de la Llave, México, Baja California, Chihuahua, Oaxaca, Guerrero, Puebla, Hidalgo, and Sonora); the interaction of gender and risk aversion (female , male) X (risk-averse, risk-taker).

a positive impact on income, as does the level of schooling. Regarding age, it has a negative effect on income for non-migrants and the overall group, but the opposite is true for migrants.

A key finding is the effect of risk aversion, measured through a risk-aversion dummy variable. This result aligns with model predictions: a risk-averse individual expects a higher income compared to their non-migrant, risk-averse counterpart. For a risk-averse person to migrate, the expected payoff from the migration process must be significantly higher to justify the associated risks.

Overall, the determinants for all groups are significant, and that allow us to move forward to the next stage of the analysis, where we need to compare groups of migrants and non-migrants to have a clear idea of how the interaction with the context affect the individuals and their migration decision. The first comparison will be done by looking at the results from the Kernel distributions results, and the graphs of their difference.

Empirical studies, such as Chiquiar and Hanson (2005) and Fernández-Huertas (2011) add further nuance to these theoretical predictions of the self-selection model by exploring intermediate selection and the role of unobservable characteristics. For example, Chiquiar and Hanson (2005) found evidence of intermediate or positive selection for Mexican migrants to the United States, which aligns with the patterns observed in risk-takers in this analysis. However, Fernández-Huertas (2011) argues that earlier findings of positive selection might overlook unobservable characteristics and suggests that negative selection could occur under different assumptions, such as higher migration costs for low-income individuals. The observed differences in self-selection between risk-averse and risk-takers in this analysis highlight the importance of considering heterogeneity in risk preferences alongside income levels when applying theoretical models like the Roy framework.

Additionally, Borjas et al. (2018) emphasize that self-selection can involve stochastic dominance relationships between migrants and non-migrants, where migrants' earnings distributions dominate non-migrants in the origin country, reflecting a nuanced view of positive selection. This analysis finds such patterns more strongly for risk-takers, where higher-income individuals dominate the migrant pool, while risk-averse individuals exhibit weaker dominance due to barriers or aversion to uncertainty. These findings emphasize the critical role of risk preferences, migration costs, and informational barriers in shaping

Table 7: Results, Monthly income (ln) regressions (all)

	(1) Monthly income (ln) All	(2) Monthly income (ln) No Mig	(3) Monthly income (ln) Mig
Family	-0.0564**	-0.0564**	0.163**
	(0.0005)	(0.0005)	(0.0166)
Mig State	-0.0881**	-0.0881**	-0.0882**
	(0.0001)	(0.0001)	(0.0041)
Separated	0.143**	0.143**	0.287**
	(0.0004)	(0.0004)	(0.0187)
Divorced	0.147**	0.147**	0.133**
	(0.0005)	(0.0005)	(0.0263)
Widowed	-0.0440**	-0.0438**	-0.281**
	(0.0004)	(0.0004)	(0.0153)
Married	-0.0589**	-0.0588**	-0.120**
	(0.0002)	(0.0002)	(0.0051)
Single	-0.0280**	-0.0279**	-0.188**
	(0.0003)	(0.0003)	(0.0131)
NA	-0.549**	-0.549**	
	(0.0087)	(0.0087)	
Rural	0.158**	0.158**	0.303**
	(0.0001)	(0.0001)	(0.005)
Schooling	0.0467**	0.0467**	0.0261**
	(0.0000)	(0.0000)	(0.0002)
age	-0.0227**	-0.0227**	0.00116**
	(0.0000)	(0.0000)	(0.0001)
Gov. Support	-0.225**	-0.225**	
	(0.0004)	(0.0004)	
Mig	0.458**		
	(0.003)		
Risk averse	5.901**	5.900**	7.385**
	(0.0001)	(0.0001)	(0.00384)
Constant	1.814**	1.815**	0.594**
	(0.0006)	(0.0006)	(0.0186)
FE	No	Yes	Yes
Observations	1308355698	1307343916	1011782
Adjusted R^2	0.478	0.478	0.792

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

migration patterns, suggesting a need to refine theoretical models to account for these complexities. This analysis confirms many foundational predictions of migration theory but also highlights deviations, particularly for risk-averse individuals, where barriers and aversion to uncertainty diminish the degree of positive selection. These deviations suggest that incorporating heterogeneity in preferences and contextual barriers into migration models could better capture real-world migration patterns.

Figure 4 The analysis begins with all individuals in the 3-year sample and then distinguishes between risk-averse individuals and risk-takers.[8]. This approach provides a clearer representation of the distributions, enabling easier comparisons without compromising significance or representativeness.

The first level of analysis involves comparing the income distributions of migrants and non-migrants across three key reference years—2007, 2012, and 2017—and disaggregating the results by risk aversion profile. While Kernel density estimates provide a detailed, non-parametric view of the distributional patterns in Figure4, they are often insufficient on their own to conclusively determine the direction of selection bias. To address this limitation, in Figure 5, kernel density difference plots—calculated as the difference between the densities of migrants and non-migrants—are used to highlight where significant divergences occur across the income distribution. These difference plots help identify whether selection is positive (migrants dominate at higher incomes), negative (non-migrants dominate), or intermediate (mixed dominance across segments).

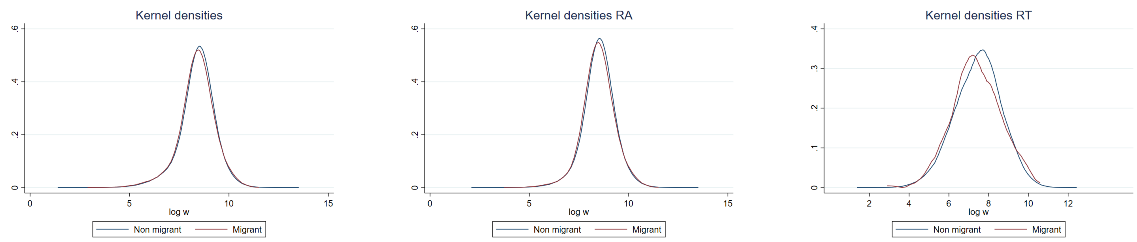
From this analysis, the results indicate a clear pattern of positive selection among risk-averse individuals, especially in later years. The income distributions for this group show a consistent rightward shift for migrants compared to non-migrants, suggesting that risk-averse individuals who choose to migrate tend to come from higher-income brackets, consistent with the idea that they require greater economic incentives to offset perceived risks. In contrast, the evidence for risk-takers is less conclusive. While some differences appear, the patterns lack consistency across years and income ranges, making it difficult

[8]The kernel density estimations were performed in Stata using bandwidths ranging from 0.15 to 1, increasing in increments of 0.1 to assess whether the relationship between the density functions remained consistent throughout the analysis. Ultimately, the presented graphs were estimated with a bandwidth of 1, as it provided smoother curves while preserving the relationships needed for comparison. Also, the estimations were made with the ”epan2” option

to assert a definitive selection mechanism for this group. This ambiguity may reflect the broader range of factors influencing migration among risk-takers, such as informal networks, aspirations, or tolerance for uncertainty that are not fully captured by income distributions alone.

Figure 4: Kernel distributions estimation (All)

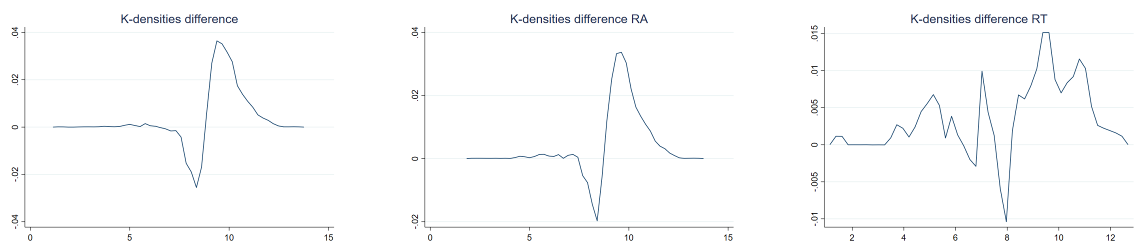
(a) **(b)** **(c)**



Source: ENOE, INEGI.

Figure 5: Kernel distributions difference (All)

(a) **(b)** **(c)**



Source: ENOE, INEGI.

Kolmogorov–Smirnov (K-S) tests were conducted to statistically assess whether the income distributions of migrants and non-migrants differ significantly across groups. For the overall population, the null hypothesis of equal distributions was rejected with a p-value of 0.000, indicating a statistically significant difference. Additionally, to validate the observed differences in mean income, a bootstrap test with 1,000 replications was conducted using the natural logarithm of income (*ln_ingocup_1*)[9]. The results confirm a

[9]The bootstrap test is a non-parametric resampling method used to assess whether the differences in distributions between two groups—such as migrants and non-migrants—are statistically significant. By repeatedly

statistically significant difference in average income between migrants and non-migrants: the mean difference was estimated at -0.036 (with non-migrants earning more on average), the standard error was 0.016, and the p-value was 0.025. The 95% confidence interval ranged from -0.067 to -0.004, confirming that the observed difference is unlikely to be due to sampling variability.

When disaggregated by risk aversion profile, the K-S test yielded a p-value of 0.000 for the risk-taker group, providing strong evidence of distributional divergence consistent with the patterns observed in the kernel density analysis. In contrast, for the risk-averse group, the p-value was 0.130, indicating that the null hypothesis of equal distributions cannot be rejected at the 95% confidence level, though it is rejected at the 90% level. These findings reinforce the importance of behavioral segmentation in the analysis and support the robustness of the observed selection patterns.

This finding supports the presence of selection bias between the groups, with non-migrants exhibiting higher mean pre-migration income in the pooled sample. Although the direction of this bias appears negative at the mean, it aligns with the more nuanced patterns observed in the kernel analysis, where both positive and intermediate selection were identified depending on the subgroup and year.

In Figure 6, the Kernel density comparisons are presented for the overall population, disaggregated by year. As in the previous exercise, the analysis begins with a comparison of the distributions, followed by the examination of their differences in Figure 7, in order to assess the presence and nature of self-selection. For the year 2007 and 2012, the results indicate clear evidence of positive selection, as migrants are overrepresented in the upper end of the income distribution relative to non-migrants. However, in the later year — 2017— the pattern becomes more complex. Migrants appear to be overrepresented around the lower and upper segments adjacent to the mean, but with a notable dip at the very center of the distribution.

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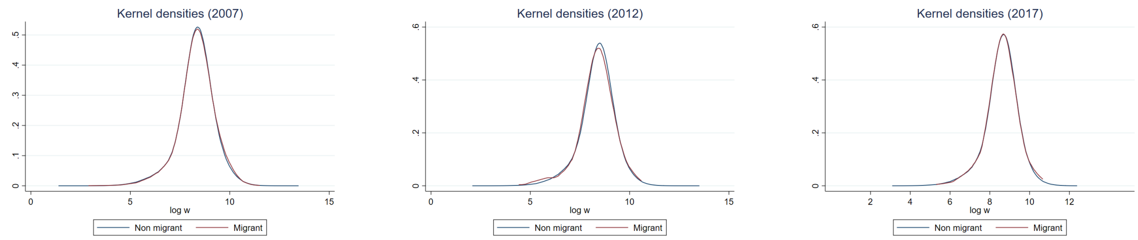
resampling the original data with replacement and recalculating a test statistic (e.g., mean difference, median difference, or a Kolmogorov–Smirnov-type distance) for each resample, the bootstrap generates an empirical distribution of the test statistic under the null hypothesis. This allows for the estimation of confidence intervals and p-values without assuming a specific parametric form. In the context of migration analysis, the bootstrap can be used to determine whether observed differences in income distributions between groups are likely to have occurred by chance, thereby providing evidence of selection bias when differences are statistically significant.

Figure 6: Kernel distributions estimation (All) by year

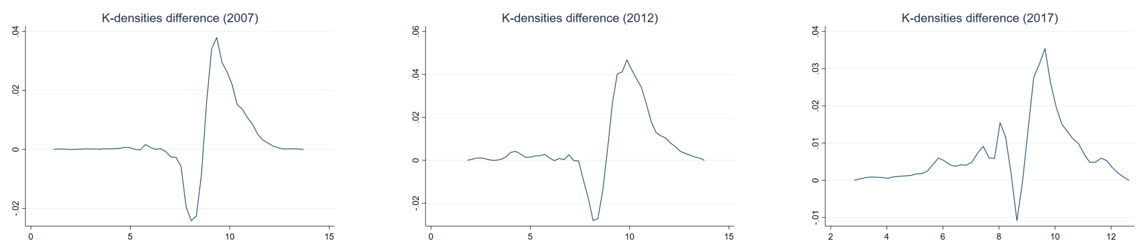
(a) **(b)** **(c)**



Source: ENOE, INEGI.

Figure 7: Kernel distributions difference (All) by year

(a) **(b)** **(c)**



Source: ENOE, INEGI.

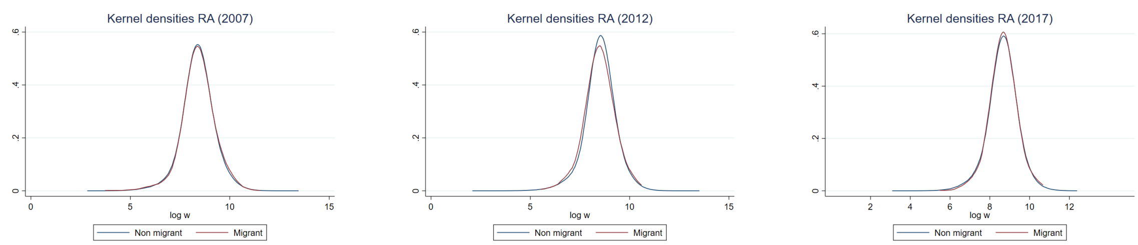
This shape suggests a non-standard form of intermediate selection, where migrants are more likely to come from both slightly below and slightly above the mean, but not from the exact middle or extreme tails. While this could be interpreted as a rare case of dual-sided selection around the central mass of the distribution, it is also important to consider the potential influence of sample size limitations, as noted earlier in the data limitations section. Nevertheless, the observed patterns provide sufficient evidence to suggest that intermediate to positive selection is present—albeit in a less conventional form—for 2012 and 2017.

In Figure 8, the first disaggregation of Kernel density estimates by risk aversion profile and year is presented, focusing on risk-averse individuals. The corresponding kernel density differences are shown in Figure 9. For the year 2007, the pattern of positive selection remains clearly visible, with migrants concentrated at higher income levels compared to non-migrants. However, for 2012 and 2017, the selection pattern becomes more nuanced and resembles what was previously observed in the overall population for 2017.

In these later years, migrants are overrepresented in regions adjacent to the mean, but not at the exact center of the income distribution. This suggests a form of intermediate selection, where migrants tend to come from both the lower and higher ends surrounding the average income, but not from the extreme tails or the very middle. This pattern points to a more complex self-selection dynamic among risk-averse individuals, where economic incentives are strong enough to influence migration, but are filtered through a more cautious approach to risk and uncertainty.

Figure 8: Kernel distributions estimation (RA) by year

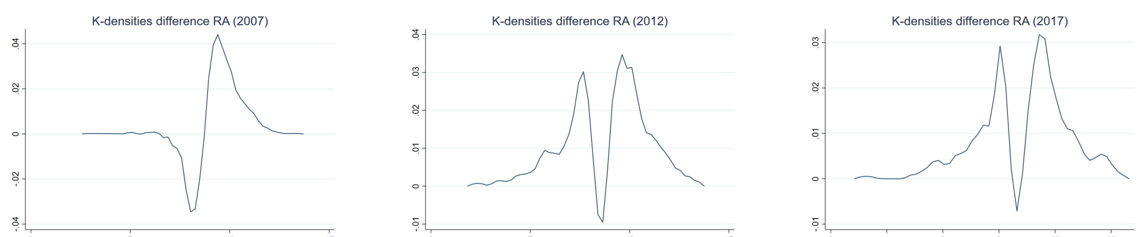
(a) **(b)** **(c)**



Source: ENOE, INEGI.

Figure 9: Kernel distributions difference (RA) by year

(a) **(b)** **(c)**



Source: ENOE, INEGI.

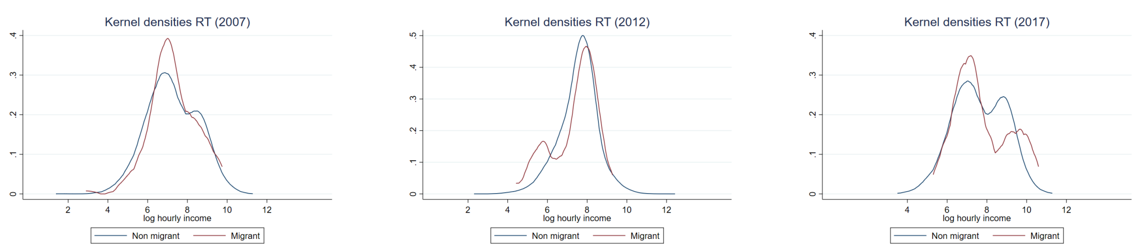
For the risk-taker group, the analysis becomes more complex, as the available tools do not allow for a clear identification of selection bias. The Kernel density estimates suggest subtle differences in income distributions between migrants and non-migrants, but the kernel density difference plots fail to reveal any consistent or discernible pattern of selection. The absence of a clear trend—whether positive, negative, or intermediate—prevents drawing firm conclusions regarding self-selection in this group.

This inconclusiveness may be partially attributed to sample size limitations, as noted earlier, which reduce the statistical power of the analysis to detect meaningful distributional differences. To further investigate potential selection dynamics among risk-takers, additional statistical testing was conducted. A bootstrap test with 1,000 replications was performed to evaluate whether the mean income difference between migrants and non-migrants in this group was statistically significant. The observed difference was 0.119, suggesting that, on average, migrants had higher incomes. However, the standard error was relatively large (0.228), and the resulting p-value of 0.602 indicated no statistically significant difference between the groups. The 95% confidence interval ranged from -0.328 to 0.566, confirming that the observed mean difference could plausibly be zero or even negative.

These findings are consistent with the earlier kernel-based analysis, which also failed to identify a clear selection pattern for risk-takers in 2017. The combination of high variability, lack of statistical significance, and flat difference plots suggests that either selection dynamics are weak or highly heterogeneous within this subgroup—potentially reflecting behavioral diversity not captured by income alone.

Figure 10: Kernel distributions estimation (RT) by year

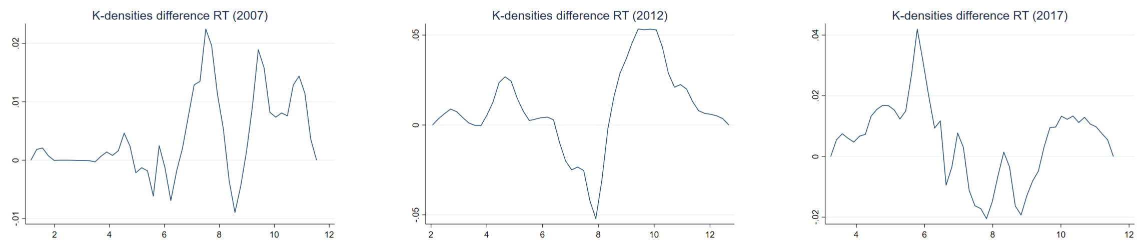
(a) **(b)** **(c)**



Source: ENOE, INEGI.

Figure 11: Kernel distributions difference (RT) by year

(a) **(b)** **(c)**



Source: ENOE, INEGI.

To add another layer to the analysis, the next step involves comparing risk aversion profiles by gender. In Figure 12, the Kernel density estimates for men show a visible pattern of positive selection in both 2007 and 2012, as migrants are more concentrated in the upper end of the income distribution. However, for 2017, the pattern is less clear, and no definitive selection bias can be concluded from the density plots alone.

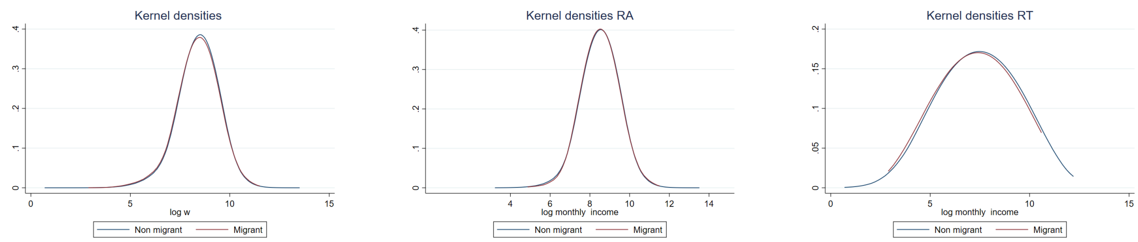
Turning to the kernel density difference plots in Figure 13, the results help to confirm the earlier findings. The positive selection observed in 2007 is clearly reinforced, and for 2012, the difference plot also suggests a strong positive selection pattern. In contrast, the 2017 results resemble those seen in the earlier overall analysis: migrants appear to be overrepresented at both the lower and upper segments of the income distribution, but not at the center. This uneven distribution, combined with the smaller sample size, makes it difficult to conclusively characterize the selection as either positive or intermediate. The pattern may reflect a sampling issue rather than a distinct selection mechanism, and further disaggregation would be needed to clarify this result.

For the women's group, the selection pattern differs notably from that observed for men, as shown in Figures 14 and 15. Figure 14 presents the Kernel density comparisons, where a clear pattern of positive selection is evident in 2007, while 2012 shows indications of negative selection. However, for 2017, the distributions overlap in a way that prevents drawing any firm conclusions based on the density curves alone.

To clarify these findings, the kernel density difference plots in Figure 15 are particularly useful. They reinforce the patterns observed in the densities: for 2007, the overrepresen-

Figure 12: Kernel distributions estimation (Men)

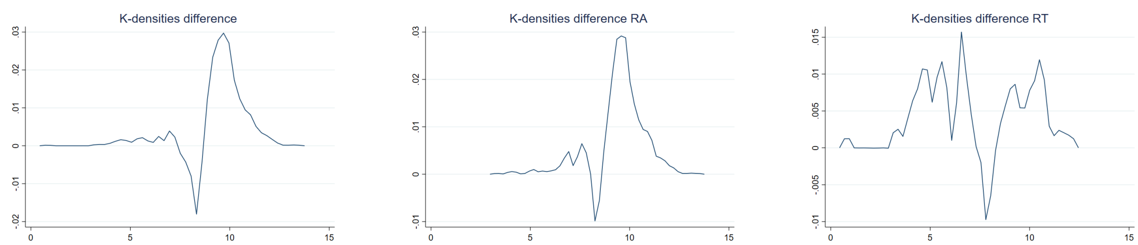
(a) **(b)** **(c)**



Source: ENOE, INEGI.

Figure 13: Kernel distributions difference (Men)

(a) **(b)** **(c)**



Source: ENOE, INEGI.

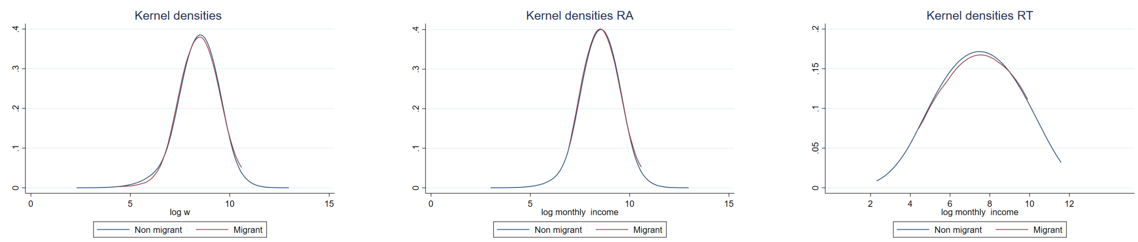
tation of migrants at higher income levels confirms positive selection, while for 2012, the dominance of non-migrants in the upper tail indicates negative selection. As with the analysis for men, the results for 2017 are inconclusive. The irregularities in the difference plot suggest a sampling issue, making it difficult to characterize the selection mechanism for that year with confidence.

The analysis reveals heterogeneous patterns of selection bias in migration decisions by comparing income distributions between migrants and non-migrants across subgroups and survey years. Using kernel density estimations, difference plots, and bootstrap tests, the results show how risk preferences, gender, and time interact in shaping selection.

For the overall population, there is strong evidence of positive selection in 2007, while in 2012 and 2017, the data suggest intermediate selection, with migrants overrepresented

Figure 14: Kernel distributions estimation (Women)

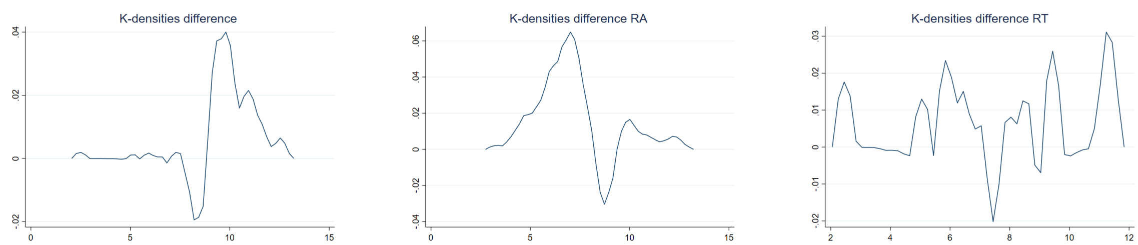
(a) **(b)** **(c)**



Source: ENOE, INEGI.

Figure 15: Kernel distributions difference (Women)

(a) **(b)** **(c)**



Source: ENOE, INEGI.

near the center of the income distribution. Bootstrap tests confirm significant differences in means.

Among risk-averse individuals, the results indicate clear positive selection in 2007 and patterns of intermediate selection in subsequent years. This suggests that these individuals migrate when the expected income return justifies the perceived risk.

In contrast, risk-takers show no consistent pattern across the three years. Both the graphical and statistical results are inconclusive, likely due to sample size limitations and behavioral heterogeneity within this group.

When analyzing by gender, men exhibit clearer positive selection in 2007 and 2012, with weaker patterns in 2017. Women, however, show more variability: positive selection in 2007, negative in 2012, and inconclusive results in 2017. These differences highlight how both gender and risk preferences shape migration behavior in distinct ways.

In sum, the findings suggest that selection into migration is not uniform. Risk-averse individuals and men show more structured selection patterns, while risk-takers and women display greater variability, likely influenced by contextual barriers and unobserved factors.

Risk aversion analysis

The novelty of this exercise lies in incorporating an explicit measure of risk aversion to identify individuals, enabling the analysis of differences between those willing to face higher migration costs while considering their demographic distinctions. This approach highlights how individuals internalize risk differently in their decision-making processes. The weight assigned to various characteristics can vary, meaning individuals must self-identify the factors that play a crucial role in their decision to migrate, as well as the potential outcomes or dynamics following migration. Therefore, understanding these individual differences is essential to examining how decision-making is influenced by risk aversion profiles and how these profiles shape migration behaviors.

$$RAI_i = \alpha + \beta_i X_i + years_i + u_i \tag{9}$$

Where RAI_i is the dependent variables that represent the risk aversion index, α is the intercept, X_i is the vector of demographic characteristics, $years_i$ is the dummy variable for the year and u_i is the error term. The regression is run for migrants and non-migrants by using a control variable, and the results are presented in table 5.

The regression results presented in Table 9 indicate that most characteristics are statistically significant, except for government support and employment in non-specified working sectors for migrants, both of which were excluded due to insufficient observations. Notably, being a woman has a distinct impact on risk aversion: for migrant women, it positively affects the risk aversion index, whereas for non-migrant women, the effect is negative, implying that migrant women exhibit higher levels of risk aversion. A similar pattern is observed for individuals working in agriculture, with risk aversion increasing for migrants but decreasing for non-migrants.

In general, demographic characteristics such as having a family, living in a high-frequency migration state, being married, having one additional year of schooling, and working in manufacturing or commerce sectors have a positive effect on migration. Conversely, variables such as originating from a rural municipality, being one year older, working in the services sector, and receiving government support show a negative effect on migration decisions. These findings underscore the nuanced role of individual and contextual characteristics in shaping migration and risk aversion profiles.

Table 8: Risk aversion index regressions (non-migrants & migrants)

	(1) Risk aversion	(2) Risk aversion
Family	0.00469**	0.0482**
	(0.0000407)	(0.00107)
Women	-0.00799**	0.0679**
	(0.0000345)	(0.00177)
Migration state	0.00173**	0.0353**
	(0.0000229)	(0.000700)
Married	0.00689**	0.0398**
	(0.0000258)	(0.000786)
Rural	-0.00707**	-0.0313**
	(0.0000317)	(0.000758)
Schooling	0.00889**	0.0131**
	(0.00000229)	(0.000102)
Age	-0.00106**	-0.00281**
	(0.00000107)	(0.0000352)
Manufacturing	0.00393**	0.0163**
	(0.0000430)	(0.00108)
Commerce	0.00546**	0.0346**
	(0.0000444)	(0.00137)
Services	-0.00291**	-0.0137**
	(0.0000388)	(0.00104)
Others	-0.0000327	-0.142**
	(0.000106)	(0.00443)
Agriculture	-0.0318**	0.0388**
	(0.0000460)	(0.000883)
Not specified	0.000145	
	(0.000276)	
Gov. support	-0.0114**	
	(0.0000910)	
2007	-0.911**	-0.905**
	(0.0000260)	(0.000779)
2012	-0.00409**	0.0285**
	(0.0000296)	(0.00102)
Constant	0.923**	0.870**
	(0.0000745)	(0.00231)
Observations	181555568	127485
Pseudo R^2		

Standard errors in parentheses
+ p¡.1, * p¡0.05, ** p¡0.01

Note: the regressions use as control being migrant (or not). For the dummy variables, the base group is always when the var takes the 0 value. Construction is the base line group in the economic sectors variable. The dummy for 2017 was omitted due to multicollinearity.

Conclusions

This chapter has presented a comprehensive analysis of self-selection patterns in Mexican migration to the United States, emphasizing the role of risk aversion as a key determinant in migration decisions. Drawing on theoretical frameworks from Borjas (1987), Chiquiar and Hanson (2005), and Fernández-Huertas (2011), the study incorporates an ex-ante risk aversion measure to better understand how individuals respond to economic incentives and contextual constraints when deciding whether to migrate.

The evidence presented shows that selection bias in migration is far from uniform. For the overall population, results from Kernel density estimates and difference plots reveal a clear pattern of positive selection in 2007, evolving into a more intermediate selection structure in 2012 and 2017. This indicates that migrants tend to originate from income ranges surrounding the mean, rather than from the extremes, a finding supported by statistically significant differences in income distributions as confirmed by bootstrap tests.

Among risk-averse individuals, the selection pattern is more stable. Positive selection is clearly observed in 2007, with income distributions for migrants skewed toward higher values. In 2012 and 2017, the analysis points to a sort of intermediate selection (cnsidering posible sampling limitations), where migrants are drawn from just above and below the income mean. This behavior aligns with the notion that risk-averse individuals require stronger economic incentives to offset migration risks.

Conversely, for risk-takers, the selection pattern is more ambiguous. Neither Kernel density comparisons nor difference plots provide conclusive evidence of positive, negative, or intermediate selection across the years analyzed. A 2017 bootstrap test shows a non-significant mean difference in income between migrants and non-migrants ($p = 0.602$), further reinforcing the absence of a systematic selection bias in this subgroup. This lack of clear selection may stem from smaller sample sizes or from greater heterogeneity in migration motives among risk-takers.

Gender-based disaggregation reveals further heterogeneity. Male migrants demonstrate consistent positive selection in 2007 and 2012, whereas in 2017 the pattern becomes less clear, possibly due to sampling limitations. Among women, results vary significantly by year: 2007 shows positive selection, 2012 shows negative selection, and 2017 remains inconclusive. These variations suggest that selection mechanisms differ by gender, shaped by both individual preferences and broader social constraints.

Overall, the findings underscore that migration is a heterogeneous process shaped by individual characteristics—such as gender and risk tolerance—and by macroeconomic and institutional contexts. The integration of risk aversion into the analytical framework enhances our ability to characterize different migrant profiles and provides a more refined understanding of self-selection. These insights not only contribute to the academic literature on migration but also offer useful implications for policymakers. Recognizing the diversity within migrant groups can help design more targeted and effective migration policies that account for both the motivations and the constraints faced by different populations.

These findings also engage with and extend the existing literature on migrant self-selection. In line with Chiquiar and Hanson (2005), this chapter finds evidence of positive and intermediate selection, especially among risk-averse individuals. However, the chapter adds nuance by showing that positive selection is not uniform across time or subgroups. While Chiquiar and Hanson (2005) argued that migrants are drawn from the middle of the distribution, this study demonstrates that selection can shift depending on macroeconomic context and risk profiles, especially evident in the shift toward intermediate selection in 2012 and 2017.

The results also partially support the arguments from Fernández-Huertas (2011), who found evidence of negative selection using pre-migration wages. While some negative selection is visible among women in 2012 and risk-takers with lower income in certain years, this chapter emphasizes the importance of risk attitudes and demographic segmentation in producing these patterns. The absence of a clear selection pattern for risk-takers aligns with Fernandez-Huertas's findings about the variability in unobservable characteristics and further validates the need for disaggregated analysis.

Lastly, this work contributes to the conversation initiated by Borjas (1987) and Borjas et al. (2018) on the role of income inequality and stochastic dominance in migrant self-selection. The findings show that for risk-averse individuals and men, earnings distributions do reflect dominance patterns consistent with positive selection, while for other groups, such dominance does not hold. This reinforces the need to integrate behavioral dimensions—like risk preferences—into theoretical and empirical models to better capture the real-world diversity of migration decision-making.

This chapter also makes an important empirical contribution by incorporating an ex-ante measure of individual risk aversion into the analysis of self-selection. By doing so, it bridges a critical gap in the literature, which has traditionally assumed homogeneity in migrants' attitudes toward risk. The findings show that differences in migration decisions cannot be fully explained by observable income or education characteristics alone; rather, they are deeply shaped by subjective risk profiles. This behavioral lens not only enhances the explanatory power of self-selection models but also opens new avenues for analyzing the diversity of migration motives—especially in countries like Mexico, where heterogeneity in socioeconomic conditions is vast.

Moreover, the use of pre-migration income data and non-parametric methods such as kernel density estimation, along with robustness checks like bootstrap testing, contributes to the methodological rigor of the study. By disaggregating results across gender, time, and risk profiles, this research uncovers hidden selection dynamics that aggregate-level analyses may obscure. It also provides a framework for future studies seeking to incorporate risk aversion and behavioral heterogeneity into the study of labor migration. The results suggest that public policies aiming to manage or leverage migration flows should consider these nuanced differences among subgroups to craft interventions that are both equitable and effective.

Chapter II. Changes in self-selection patterns over time: a revision of Mexico and the U.S. migration dynamics and the effect of context shocks.

Abstract

This chapter analyzes migration self-selection patterns from Mexico to the United States between 2007 and 2017, incorporating risk preferences to better understand how individuals with varying levels of risk aversion select into migration. Using data from the ENOE and applying Kernel density estimations and income regressions, the study distinguishes between observable and unobservable characteristics among migrants and non-migrants. The findings show that risk-averse individuals tend to exhibit consistent positive selection on observable traits, especially during periods of economic uncertainty, while unobservable traits show less defined patterns. In contrast, risk-takers display more heterogeneous and unstable selection dynamics. By introducing risk tolerance into the Borjas self-selection framework, the chapter provides new insights into how behavioral traits influence migration decisions and underscores the importance of tailoring migration policy to individual-level characteristics and contextual factors.

Key concepts: self-selection; migration; human capital; skills; Mexico-U.S. ; risk aversion.

JEL classification: J31, J61, O15, R23.

Introduction

I present an analysis of self-selection patterns among Mexican migrants, examining how economic and political shifts influence migration decisions. Using data from the National Occupational and Employment Survey (ENOE) for 2007–2017, I analyze the evolution of self-selection characteristics within the framework of Borjas et al. (2018). Additionally, I incorporate risk aversion metrics based on Thomas (2016), Hanoch and Levy (1969), and Dustmann et al. (2017) to capture how perceptions of safety and security affect migration choices, particularly in the context of economic uncertainty.

I hypothesize that the self-selection patterns of Mexican migrants to the United States have adapted in response to significant economic and political shocks. Specifically, I anticipate that the 2009 global financial crisis reinforced positive selection among migrants with observable skills. The heightened economic uncertainty and migration costs likely discouraged lower-skilled individuals from migrating. Furthermore, the change in administration in Mexico in 2012 may have influenced labor mobility and migration dynamics, leading to shifts in the selection of migrants based on unobservable skills. Nonetheless, these shifts are likely the result of a complex interplay of multiple factors rather than a direct consequence of these events alone. By examining self-selection patterns over different time periods, this study seeks to reveal how migration responds to evolving economic and policy landscapes.

Migration is closely linked to economic growth, as it generates human capital externalities that enhance productivity. However, this effect depends on how migrants integrate into labor markets and productive sectors, and more specifically, on their self-selection patterns. Migration self-selection refers to how individuals choose to migrate based on education, skills, and household composition. Borjas (2019) examines this complex relationship between immigration and economic performance, noting that while migration is often regarded as a driver of growth, its actual impact varies based on factors such as skill composition, assimilation rates, and labor market integration. Moreover, the link between migration and growth is dynamic, evolving as labor market participation and self-selection patterns shift over time.

Financial constraints also play a critical role in migration decisions. As Görlach (2021) highlights, higher incomes in the home country reduce migration duration but encourage repeat migration, while borrowing constraints shape return migration and savings behavior. Beyond economic factors, public perceptions of immigration influence both policy and social attitudes. Ajzenman et al. (2021) analyze immigration and crime perceptions in Chile, showing that while migration does not increase crime rates, media coverage amplifies fears, leading to greater investments in security. Similarly, Bell et al. (2013) examine migration and crime in the UK, concluding that while immigration had minimal overall impact on crime, modest increases in property crime were observed during asylum-seeker surges. These findings suggest that economic opportunities play a key role in shaping public attitudes toward migration.

In the context of migration economics, Borjas (1987) introduces the self-selection theory, arguing that migrants from high-inequality countries tend to be positively selected, leading to higher earnings upon arrival in the destination country. This theory is further expanded by Borjas (1992), who employs a stochastic dominance framework to explain how both observable and unobservable characteristics influence migration decisions. Cadena and Kovak (2016) explore how immigrants adjust to local labor markets, arguing that migration helps equilibrate regional wage disparities, as immigrants respond to economic signals and impact labor supply across U.S. regions. B. R. Chiswick (2000) contribute to the discussion by examining whether immigrants are favorably selected for their skills, concluding that economic migrants typically exhibit higher skill levels than non-migrants, while refugees are less favorably selected due to different migration motives.

A historical lens is provided by Abramitzky and Braggion (2006), who study indentured servants to the Americas. They reveal that migrants to mainland colonies were positively selected for unobservable human capital, whereas those bound for the West Indies were negatively selected. In the context of undocumented migration, Orrenius and Zavodny (2004) find that undocumented Mexican migrants tend to be lower-skilled and are motivated by the U.S. labor market's demand for low-wage workers, highlighting how legal status shapes selection and outcomes. Kaestner and Malamud (2014) extend the discussion by showing that better educated individuals are more likely to migrate legally, driven by economic incentives and migration costs. Furthermore, Kleven et al. (2020) discuss how taxation affects migration, particularly for high-income individuals, arguing that tax differentials can undermine tax revenues, highlighting the need for coordinated global tax policies.

Massey and Gentsch (2014) focus on the vulnerability of undocumented migrants, attributing their wage suppression to rising competition and stricter immigration policies post-1986. Lessen (2017) complements this by exploring the effects of U.S.-Mexico wage differentials and border enforcement on immigration flows. He concludes that while stricter enforcement reduces illegal migration, the economic disparities between the two countries remain significant migration drivers. Furthermore, Orrenius and Zavodny (2004) explore how stricter enforcement impacts employment and wages for Latin American immigrants, finding that these policies led to declining wages and job prospects for recent migrants, particularly post-9/11.

Economic growth in host countries is also influenced by immigration, as Aleksynska and Tritah (2014) demonstrates through their study of 20 OECD countries. They find that while younger immigrants may initially depress income, they contribute to medium-term productivity gains as they integrate into labor markets, highlighting the long-term benefits of immigration. Temporary migration, as Clemens (2013) notes, can alleviate labor shortages in receiving countries, although it presents challenges, such as the exploitation of migrants and reintegration difficulties when they return to their home countries.

Migration dynamics are not solely driven by economic factors. Urbanski (2022) analyzes push and pull factors that influence migration between Poland and Romania, finding that pull factors, such as economic opportunities and political stability, are stronger motivators than poverty or political instability. The accumulation of human and social capital related to specific entry modes also shapes migration patterns. Wassink and Massey (2022) describe the emergence of a new migration system between Mexico and the United States, dominated by temporary legal labor migration. They argue that U.S. immigration policies and labor market demands have shifted the predominant mode of entry from undocumented migration to the use of temporary work visas, further shaping migration outcomes.

Borjas (1987, 1992) and Borjas et al. (2018) explores how self-selection influences the earnings of immigrants, focusing on why immigrants from specific countries earn different wages in the U.S. Borjas argues that immigrants are not homogeneous; rather, they self-select based on individual characteristics like education, skills, and motivation. Fernández-Huertas (2011) adds to this discussion by showing that during 2000–2004, Mexican emigrants to the U.S. were negatively selected, which means that they were generally less productive than non-migrants. This was evident in the wage distributions of migrants and non-migrants, with the ENET survey highlighting the differences.

Chiquiar and Hanson (2005) challenge the notion of negative selection, finding that Mexican immigrants in the U.S. tend to be more educated than non-migrants in Mexico, and would fall within the middle or upper parts of Mexico's wage distribution if they returned. Mishra (2007) similarly finds a positive relationship between emigration and wage increases in Mexico, estimating that a 10% reduction in the labor force due to emigration is associated with a 4% wage increase for those remaining, though this effect may widen wage disparities. Both studies highlight the nuanced impact of migration on wage structures, as also noted by McKenzie et al. (2010), who emphasize the role of migration networks in shaping Mexican migration dynamics.

Durand et al. (2001) track the shifts in the composition of Mexican migrants, noting a transition from rural to urban migrants, with increasing educational diversity over time. Escamilla-Guerrero and López-Alonso (2022) examine how economic shocks, such as the Panic of 1907[10], influenced Mexican migrant self-selection, showing that economic crises can change the nature of selection from negative to positive. Monras (2015) similarly revisits the 1994 Mexican Peso Crisis, showing that wage reductions following the influx of low-skilled migrants were temporary, with labor market adjustments eventually restoring balance.

G. H. Hanson and Liu (2021) explore the home-country determinants of migration success, noting that foreign-born workers often select occupations based on their country of origin's educational quality and linguistic similarities. Migration networks further aid this process by providing critical information and helping to allocate migrants within labor markets. Hendricks (2001) emphasizes that ethnic clustering within labor markets serves

[10]This was a severe financial crisis that occurred in the United States. It was triggered by the San Francisco earthquake in 1906, which caused significant damage and led to large amounts of gold flowing from London to the United States; characterized by a sell-off of securities, a reduction in the U.S. gold stock, and a recession in the economy.

as a proxy for skills validation, helping migrants access benefits similar to those of their peers.

Chort and de la Rupelle (2016) examine how migration networks and geographic distribution impact migration, arguing that regions with robust historical migration ties have networks that lower costs, reduce risks, and provide vital information to new migrants. They also note that safety and security, alongside environmental factors, can act as shocks that trigger migration. Between 2006 and 2012, Mexico experienced significant shifts in public security policies, leading to an aggressive response from organized crime and a subsequent shift in public safety perceptions. These changes, particularly following a leadership transition, initially improved safety perceptions, but this effect was short-lived. The initial shift, however, acted as a temporary shock that influenced migration decisions.

Understanding the dynamic patterns of migration self-selection is critical for policy makers and researchers seeking to understand how migration affects both origin and destination countries. The constantly evolving contexts in Mexico and the U.S. drive variations in migrant composition, influencing self-selection characteristics. These changes in selection patterns may lead to different outcomes, which necessitate adjustments in migration policy. This research aims to address these dynamics and offer conclusions about the evolving self-selection patterns of Mexican migrants.

Theoretical framework

Self-selection Model

Migration, as a form of human capital investment, occurs when individuals aim to maximize their returns by selecting destinations offering the most favorable opportunities. This idea, first proposed by Sjaastad (1962), suggests that migrants assess the value of opportunities at various destinations, choosing the one that maximizes their returns. Building on Sjaastad's work, Borjas (1987) introduced the self-selection framework, which argues that migration decisions are influenced by income-maximization behavior and income inequality. Suggesting that when income inequality is higher in the source country, such as between Mexico and the U.S., migrants tend to be negatively selected, meaning they are less skilled than those who remain. Borjas (1991) refined this model, showing that positive selection occurs when skilled individuals migrate to countries with higher rewards for skills, while negative selection dominates when low-skilled individuals migrate from more unequal societies.

Recent studies have emphasized the role of individual characteristics, such as risk attitudes, in migration decisions. Jaeger et al. (2010) provide direct evidence that individuals who are more willing to take risks are significantly more likely to migrate. Their research, based on data from the German Socio-Economic Panel, suggests that risk attitudes have a larger effect on migration probabilities than traditional factors such as age, sex, or education. This finding supports the idea that migration is inherently risky and that individuals with higher risk tolerance are more inclined to pursue migration as a means of improving economic opportunities.

Empirical research has tested Borjas's self-selection model, yielding mixed results. Chiquiar and Hanson (2005) challenged the negative-selection hypothesis, finding that Mexican migrants to the U.S. in the late 1990s were drawn from the middle and upper segments of Mexico's wage distribution, indicating positive or intermediate selection. However, Fernández-Huertas (2011), using pre-emigration wage data from the National Quarterly Employment Survey (ENET by its acronym in Spanish), found evidence of negative selection among Mexican emigrants between 2000 and 2004, attributing the differences in their findings to methodological approaches. Fernández-Huertas (2011) also explored gender differences, finding that male Mexican migrants were less educated than non-migrants, while female migrants had more schooling, indicating positive selection for women. Caponi (2011) further examined education and migration, revealing a U-shaped pattern, where the least educated and most educated individuals are more likely to migrate, while those in the middle are less likely to emigrate.

Migration networks also shape the self-selection process. McKenzie et al. (2010) demonstrated that stronger migration networks increase the likelihood of negative selection by lowering migration costs for low-skilled individuals. In areas with established networks, lower-skilled migrants benefit from reduced migration costs and social support, whereas higher-skilled individuals are less reliant on such networks. Munshi (2003) supported this view, showing that networks help low-skilled Mexican migrants secure higher-paying jobs in the U.S., thus facilitating their migration.

Wage differences further highlight the self-selection process. Fernández-Huertas (2011) emphasized that Mexican emigrants earned lower wages before migration compared to non-migrants, supporting the negative-selection hypothesis. These findings contrast with Chiquiar and Hanson (2005) analysis, which indicated higher productivity among Mexican migrants. Fernández-Huertas (2011) attributed this discrepancy to methodological differences, particularly the undercount of undocumented migrants. Borjas (1987) also noted that negative selection often results in lower earnings for migrants in the destination country, as low-skilled individuals face greater challenges in adapting to the labor market. Nonetheless, even negatively selected migrants can contribute significantly to the host economy by filling labor shortages, as Fernández-Huertas (2011) concludes.

As Escamilla-Guerrero and López-Alonso (2022) mention, economic and political shocks can significantly influence the self-selection patterns of migrants by altering both the incentives and constraints associated with migration. The 2008–2009 global financial crisis, for example, introduced heightened economic uncertainty, particularly in key migrant-receiving economies such as the United States. During periods of economic downturn, employment opportunities shrink, and the relative costs of migration increase, which may deter lower-skilled individuals who are more vulnerable to economic instability and lack the necessary resources to migrate. This mechanism could reinforce positive selection, as only individuals with lower levels of risk aversion, higher skill levels, better financial resources, or stronger networks may be able to absorb or process the risks and costs associated with migration during crises. Conversely, in the aftermath of the crisis, economic recovery could have different effects depending on whether labor demand rebounds more strongly in high - or low-skill sectors.

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Between 2009 and 2012, migration dynamics between Mexico and the United States underwent significant changes due to economic conditions, policy shifts, and evolving migration trends. In 2009, during the peak of the Great Recession, the U.S. experienced substantial job losses in sectors that traditionally employed Mexican migrants, such as construction and manufacturing. This economic downturn led to a notable decrease in Mexican migration to the U.S., with more individuals returning to Mexico than arriving, as Pew Research Center (2015) indicate. Concurrently, the Obama administration intensified deportation efforts through programs like Secure Communities, resulting in record numbers of removals, according to Migration Policy Institute (2013).

Political changes in the sending country can reshape migration dynamics by affecting labor market conditions, institutional stability, and migration policies. For instance, the 2012 change in administration in Mexico introduced shifts in economic and security policies that may have influenced labor mobility and migration incentives. Political transitions often create uncertainty in governance and economic policy, leading to fluctuations in job availability, wage structures, and public investment—all of which influence migration decisions. In this sense, if the new administration implemented policies that improved domestic labor opportunities, migration pressures could have decreased, potentially discouraging lower-skilled workers from leaving. Conversely, if governance changes were linked to rising insecurity or economic instability, migration flows might have increased, with selection patterns varying depending on which segments of the population were most affected and their risk aversion profiles. In both cases, the interaction between economic and political factors plays a crucial role in determining who migrates and under what circumstances.

Beyond domestic political shifts in Mexico, broader economic and policy changes in the U.S. also influenced migration trends. By 2012, as the U.S. economy showed signs of recovery, migration from Mexico remained low, a trend influenced by improving economic conditions in Mexico, which reduced incentives to migrate Pew Research Center (2015). Additionally, the Obama administration implemented the Deferred Action for Childhood Arrivals (DACA) program in June 2012, offering temporary relief from deportation and work authorization to undocumented immigrants who arrived as children American Immigration Council (2021). Furthermore, the 2012 U.S. presidential election generated significant debate on immigration policies, creating uncertainty among undocumented migrants Migration Policy Institute (2013). These combined factors marked a shift away from traditional Mexican labor migration toward a more complex regional migration dynamic.

Although various factors shape migration decisions, it is essential to acknowledge that Mexican residents contemplating migration base their choices primarily on domestic conditions and firsthand information available to them. In this sense, political and economic changes within Mexico were likely among the most significant contextual factors shaping migration dynamics. Given the risk aversion profiles of potential migrants and the labor market conditions at the time, shifts in economic stability, security, and governance may have played a decisive role in altering migration incentives and selection patterns.

Following the same approach as Borjas et al. (2018), Chiquiar and Hanson (2005), Fernández-Huertas (2011), and others, in this chapter, an assessment of the selection bias in the Mexico and the U.S. migration dynamics is presented with the incorporation of an ex-ante risk aversion measure that will allow for a better understanding of the decision-making process. For doing the previous, the first step is to define the model that will describe the migration process in terms of income.

The two main equations that define the decision-making process are:

$$ln(w_{0i}|\overline{\lambda_i(w_{0i}, C_i^*)}) = \alpha_{0i} + r_{0i}s + \eta_{0i} \tag{10}$$

$$ln(w_{1i}|\overline{\lambda_i(w_{1i}, C_i^*)}) = \alpha_{1i} + r_{1i}s + \eta_{1i} \tag{11}$$

Where w_i is the wage in the i country; λ_i represents the level of risk aversion, i.e., the risk aversion profile, for the person i; C_i^* is the level of migration costs for each person;

r_i is the rate of return of observable skills; η_i the individual specific productivity shocks resulting from the unobserved characteristics, with $\eta_i \sim N(o, \sigma_i^2)$; where $i = 1, ..., N$, 0 represent the home country ad 1 represent the host country. The distribution of observable skills in the source country in the origin country is $s = \mu_s + \varepsilon_s$, where the random variable $\varepsilon_s \sim N(0, \sigma_s^2)$.[11]

The previous equations fully describe the earnings opportunities in both the origin and destination countries. The migration decision is influenced by the individual's risk aversion profile. Specifically, when $\lambda = 0$, the individual is a risk-taker; when $\lambda = 1$, the individual is risk-averse. This ex-ante measure of risk aversion allows for the categorization of individuals and contributes to a clearer understanding of how migration determinants shape decision-making—particularly in how individuals, depending on whether they are risk-takers or risk-averse, interpret and respond to their contextual environment. Therefore, the migration decision can be expressed through the comparison of earnings levels using the following index function:

$$\begin{aligned} &I = log(\tfrac{w_{1i}}{w_{0i}+Ci^*}) \\ &\approx [(\alpha_{1i} - \alpha_{0i}) + (r_{1i} - r_{0i})\mu_{si} - \pi^*] + [(r_{1i}\varepsilon_{si} + \varepsilon_{1i}) - (r_{0i}\varepsilon_{0i} + \varepsilon_{0i})] \\ &= \Delta\mu + (v_{1i} - v_{0i}) > 0 \Rightarrow \quad \textbf{migration} \quad \textbf{occurs} \end{aligned} \tag{12}$$

Where $\pi^* = C^*/w_{0i}$ represent the time-equivalent migration costs; $\Delta\mu = (\alpha_{1i} - \alpha_{0i}) + (r_{1i} - r_{0i})\mu_{si} - \pi^*$ is the cross difference in earnings net the time-equivalent migration costs fro an individual with average observed and unobserved skills; and $(v_{1i} - v_{0i})$, where $v_{ji} = (r_{ji}\varepsilon_s + \varepsilon_{ji)}$, where $j = \{0 : home, 1 : host\}$, is the difference in earnings due to individual deviations from average characteristics.

Given the risk aversion profile defined by the λ risk aversion identifier within the group and their respective distributions, it is possible to define comparison groups according to a similar set of characteristics for the decision-making process. In that sense, it is possible

[11]For convenience we assume $cov(\varepsilon_0, \varepsilon_s) = cov(\varepsilon_1, \varepsilon_s) = 0$, so that the individual-specific unobserved productivity shock are uncorrelated with the observable characteristics. The correlation between ε_0 and ε_1 is equal to ρ_{01}, where rho represents the correlation between two variables.

to say that the decision-making process has been refined due to the incorporation of a risk measure that varies from individual to individual and from group to group; therefore, there are different types of migrants and non-migrants that consider the context and their characteristics and how this impact in these has an effect in the migration decision.

The latter allows us to understand the relationship between risk aversion, migration costs, and the characteristics of individuals. In the sense that intuitively a person with a better context will face less non-monetary costs to consider in the decision to migrate, i.e., a better level of skills, less credit constraints, assets in the home country, a shared responsibility in the origin country household, better physical capabilities (lower probability of getting hurt or sick during the migration or overseas process, etc.) for migration, should be able to face better the cost associated with the decision of migrate, and therefore be less risk-averse to initiate the migration process (Sjaastad, 1962). Adding earnings to the process will enhance the prediction about the migration decision, that is, a person with a better context will be less risk-averse and with higher earnings will face the migration process more easily or even without concerns. The previous works the same for legal and illegal migration.

Borjas identified and established a negative selection bias within Mexico-U.S. migration, indicating that individuals from the lower end of the skills distribution are more likely to migrate to the U.S. However, migration is fundamentally a human capital investment decision, and following Sjaastad's approach, attitudes toward risk are crucial in shaping this process. In this context, an ex-ante measure of risk aversion is essential for understanding the differences between individual profiles in the sending country, as well as the main reasons and characteristics influencing their decision to migrate.

Risk aversion profiles deepen the analysis of individuals' decision-making processes and contexts. Risk-tolerant individuals are more likely to migrate, even with lower income expectations, due to their personal characteristics and circumstances in the sending country. Conversely, risk-averse individuals typically have higher income expectations, shaped by their self-assessment of their skills and perceived value.

The introduction of an ex-ante classification of profiles into the model creates a two-group framework: one for risk-averse individuals and another for risk-takers. This distinction significantly affects the empirical analysis of the model.

Risk aversion

The decision-making process in the context of migration and investment under uncertainty can be viewed as a two-step procedure. First, an individual efficiently chooses among all available options without regard to personal preferences and then applies those preferences to select the option that best suits their needs (Hanoch & Levy, 1969). This framework links the concept of riskiness to migration decisions, where individuals must consider both external determinants and their own risk preferences. Consequently, understanding risk aversion is essential for explaining such decisions.

Risk aversion plays a critical role in decision-making under uncertainty, particularly in fields such as migration and investment. Traditional utility-based approaches to risk aversion have been criticized for their limitations in capturing the complexities of human behavior. Thomas (2016) offers a more realistic approach by using dimensional analysis to understand how people make decisions in risky scenarios. This method challenges the idea that risk aversion can be understood solely through utility models, suggesting instead that risk preferences are more nuanced and context-dependent. In exploring how household wealth affects risk aversion, Brunnermeier and Nagel (2008) find that fluctuations in wealth have little impact on individuals' risk attitudes, contrary to predictions by habit-formation models. Their research shows that inertia—rather than changes in wealth—plays a greater role in determining how people allocate assets, further complicating our understanding of risk aversion in dynamic financial contexts.

Levy (1992) and later Leshno and Levy (2002) contributed significantly to the field by introducing the concept of Almost Stochastic Dominance (ASD), which addresses situations where traditional stochastic dominance rules are insufficient. ASD allows decision-makers to rank alternatives based on the preferences of the majority, making it particularly useful in finance and investment, where utility functions may vary across individuals (Leshno & Levy, 2002). This concept is valuable in decision-making under risk, especially in diverse populations where risk preferences differ.

Building on these ideas, Davidson and Duclos (2000, 2013) apply stochastic dominance to broader social issues, such as poverty and inequality. They develop robust statistical methods for comparing income distributions and measuring welfare improvements. These techniques help decision makers assess not only financial risks but also the societal impacts of economic policies. Thistle (2008) further refines the understanding of risk aversion by introducing models that incorporate negative moments and stochastic dominance principles. His work demonstrates how economic agents can make optimal decisions under uncertainty, providing a framework for evaluating choices in both migration and financial contexts.

The notion of risk aversion, as defined by Thomas (2016), is the feeling that guides a person facing uncertain outcomes—whether related to money, status, happiness, or other important life aspects. By generating a relative risk aversion measure that accounts for individual characteristics, it becomes possible to recover not only the monetary costs associated with migration but also non-monetary costs. This approach provides a more precise measure of both the costs and returns of migration, factoring in individuals' perceptions of risk and how they internalize their surrounding context (Dustmann, Fasani, et al., 2017).

To calculate this measure, a Taylor series expansion is typically used to estimate the individual's risk aversion based on their starting wealth. This method has the advantage of not requiring a specific utility function, and it accommodates changes in risk aversion during pairwise comparisons of alternatives. This approach ensures a more flexible and comprehensive assessment of how individuals evaluate risky decisions in uncertain environments. There are good reasons for considering the risk aversion to differ between individual profiles, more if we consider the heterogeneous origin of migrants in Mexico, not only because of geography, but also because of differences in the level of development and capabilities.

Let there be a lottery that offers a prize of $w_{i,1}$, that is, the wealth the agent has in the foreign country, and $w_{i,0}$ that is the initial wealth of the agent in the foreign country, where i denotes the agent. This means that the agent could have the new wealth only if she decides to migrate, that is, the wealth can only be $w_{i,1}$ or $w_{i,0}$. The previous lottery has the probability p of occurrence, therefore, the probability of non-occurrence is $1 - p$. that is, the expected utility of the lotteries is[12]:

[12]In this analysis, monthly labor income reported in the ENOE is used as a proxy for individual wealth. While ideal wealth measures would include assets and savings, such data is not consistently available in ENOE. Given the structure of the Mexican labor market and the relatively low levels of asset accumulation among the working population, monthly income serves as a reasonable approximation of financial capacity.

$$E[w_{i,1}] = p \cdot w_{1i} + (1-p) \cdot 0 = pw_{1i} \tag{13}$$

The agent has to define the threshold to identify the limit she is willing to spend or pay to migrate to another country. For this purpose, a maximum price to pay for migration is defined, $c_i = pw_{1i}$, which is also equal to $E[w_{1i}]$, the risk neutral position, that is, the risk aversion is equal to zero. With the previous, we can expect that a different maximum amount to pay will also indicate the level of risk aversion (λ), given the level of wealth or wage she has in the current country (country of origin at the moment).

Once the ticket of migration is paid, the current wealth decreases by the amount paid, leading to a new level of utility $U(w_{i,0} - c_i)$, in the case where the migration occurs, then she also wins the new wage $w_{i,1}$, if not, then she only reduces his current wage, the previous transforms the expected utility as follows:

$$E[U] = p \cdot u(w_{0i} + w_{1i} - c_i) + (1-p) \cdot u(w_{0i} - c_i) \tag{14}$$

where $w_{1i} - c_i < w_{0i}$ and $c_i < w_{1i}$. With this it is possible to expand the two terms on the right side with a Taylor expansion in order to obtain the risk aversion measure.[13]

$$-\frac{u''(w)}{u'(w)} \leq \frac{2(pw_{1i} - c_i)}{pw_{1i}^2 - 2pw_{1i}c_i + c_i^2} \tag{15}$$

Now, the individual has a way to compare if she has at least no loss without regard if she decides to migrate or not. Taking the previous result, we can multiply equation (6) by the initial wealth (the wage the agent has at the beginning a in the origin country); it is possible to obtain the relative measure of risk aversion and introduce a richer way to characterize the way the agent internalizes his context, i.e.:

$$\lambda_i \leq \frac{2w_{0i}(pw_{1i} - c_i)}{pw_{1i}^2 - 2pw_{1i}c_i + c_i^2} \tag{16}$$

This proxy aligns with prior migration and risk-aversion studies that rely on income to reflect individuals' ability to absorb migration costs and make intertemporal decisions under uncertainty (Borjas, 1987; Chiquiar & Hanson, 2005; Jaeger et al., 2010).

[13]The advantage of using a Taylor expansion is that we can generate a risk aversion measure independently of the precise utility function.

With this risk aversion equation, we can identify that two key levels of risk aversion that help us to understand the way agent behaves and takes her decision: the maximum price to pay given her wealth and characteristics and the break even point that set the threshold. For the first level, we have to identify when the inequality change direction, this will be at the point where the price is the maximum that can be absorbed in order to migrate, meaning that we have $\lambda(max|c_i, w_i)$ and from this expression we can identify the also the maximum price to pay $c_{i,max}$.[14]

Now that we know the maximum price to pay, we can set a break-even point that implies looking at the case where the inequality in (6) is an equality.

$$\lambda_{i,BE} = \frac{2w_{0i}(pw_{1i} - c_{i,max})}{pw_{1i}^2 - 2pw_{1i}c_{i,max} + c_{i,max}^2} = \frac{2w_{0i}/c_{i,max}(pw_{1i}/c_{i,max} - 1)}{p(w_{1i}/c_{i,max})^2 - 2pw_{1i}/c_{i,max} + 1} \tag{17}$$

To empirically implement this model, I use data from the ENOE (2007–2017) to recover wages for both migrants and non-migrants, construct migration probabilities by survey wave, and merge these with exogenous estimates of migration costs. The risk aversion measure derived in equation (7) is then applied at the individual level, capturing how each person weighs expected income gains against the costs and uncertainty of migration. Specifically, the measure uses observed hourly wages in the origin and destination contexts (w_{0i}, w_{1i}), the probability of migrating (p), and the estimated migration cost (c_i), allowing for the calculation of a relative risk aversion index λ_i.

To interpret this metric, I calculate a break-even threshold based on the maximum migration cost an individual can absorb, $c_{i,\text{max}}$, and derive a reference risk aversion level $\lambda_{i,\text{BE}}$ at which the agent is indifferent between migrating or staying. Individuals whose estimated λ_i falls below this break-even value are classified as risk-takers, while those with a higher λ_i are deemed risk-averse. This classification introduces behavioral heterogeneity into the migration model, enabling a richer understanding of self-selection and decision-making processes.

Furthermore, individuals are grouped into clusters based on observable characteristics—such as income level, education, and region—to assess how structural conditions

[14]It is necessary to have in mind that the risk aversion is a function of c_i and it is decreasing as c_i if, and only if, c_i is in the range $0 < c_i < c_0(1 + \sqrt{(1 - p/p)^{\frac{1}{2}}})$

shape both risk preferences and migration behavior. These groupings enable not only the comparison of migration probabilities but also the application of stochastic dominance techniques to assess how differences in context and risk aversion influence economic mobility across populations.

Risk aversion identification

Equation 7 serves as the starting point for characterizing risk aversion, as it determines each individual's level of risk aversion. As previously explained, wealth is represented by monthly income, which includes all the income registered by the individual. Using this information, along with the average level of migration costs faced during a specific period, an individual's level of risk aversion is estimated. To simplify the analysis, this is represented as an index.

The maximum migration cost paid by migrants each year, obtained from the Mexican Migration Project, is used to set a threshold for distinguishing between risk-takers and risk-averse individuals. Specifically, the level of risk aversion is calculated using this maximum cost, and individuals with a higher level of risk aversion than the threshold are classified as risk-takers, while those with a level equal to or lower than the threshold are classified as risk-averse.

This process allows for the characterization of every individual in the dataset, regardless of whether they migrate or not. This final classification is then used for analysis, resulting in the identification of both risk-averse and risk-tolerant individuals among migrants and non-migrants.

Data

In order to test the model the main data source is the ENOE, following the exercise done by Fernández-Huertas (2011) with the Encuesta Nacional de Empleo Urbano (ENEU) and the Encuesta Nacional de Empleo (ENE), I will use the consolidated project the Encuesta Nacional de Ocupación y Empleo. This data set allows us to use demographic characteristics at an individual level. although there are limitation using a survey in terms of the significance of the variables given the specifications to confirm the comparison groups, this is still one of the most reliable sources to observe and compare migrants and non-migrants groups in Mexico. Several results will be presented to ensure the robustness of the estimations. The secondary data for this exercise is the panel of the Mexican Migration Project that for this exercise provides the cost of migration that is needed for the calculation of the risk aversion measure.

Description

- ENOE
  The main data source is the National Employment and Occupation Survey (ENOE in Spanish). For this chapter, annual waves are used to differentiate migration dynamics and individual decision-making processes to assess self-selection biases in the analysis period. As mentioned, one of the key characteristics of this survey is that it can be constructed as a rotative panel that involves tracking and resurveying the same individuals and households over multiple quarters or waves (5 in total). This process creates a longitudinal dataset that allows to study changes in employment, income, and other labor market variables for the same individuals over time.

- Mexican Migration Project
  The MMP is a collaborative research project based at Princeton University and the University of Guadalajara. It is an extensive research initiative that collects and analyzes data related to Mexican migration to the United States. It focuses primarily on understanding the patterns, causes, and consequences of Mexican migration. It is a longitudinal data survey, which allows to study the dynamics of migration, including the decision-making processes, migration histories, and the impacts on both sending and receiving communities. One of the central components of the MMP is the collection of data from Mexican migrants in the United States, including demographics, economic conditions, education levels, and migration histories of household members. In addition, information about legal status, employment, remittances, and family ties on both sides of the border.

  This dataset provides information on migration costs paid across different waves, a crucial variable for developing the risk aversion measure used in this research.

By analyzing migration costs, it becomes possible to assess individual risk profiles. Additionally, the maximum migration cost—which serves as the break-even point distinguishing risk-averse individuals from risk-takers—is derived from this dataset by estimating the highest cost paid per year. These two key variables, migration cost and break-even point, are provided by the Mexican Migration Project (MMP) for this research. However, a key limitation of the panel is its level of representativeness. Despite this limitation, the dataset remains a valuable resource for understanding the financial constraints and risk attitudes of migrants.

The MMP Database (MMP134) is currently one of the most concise and vast data sets of its kind in existence. It comprises 134 communities with 21,522 households surveyed in Mexico and 957 households surveyed in the United States. Individual level data on 71,448 males and 72,805 females, for a total of 144,258 persons. It contains information about 7,398 household heads with migration experience to the U.S.. The life history file has a total of 1,082,322 of person-years for analysis.

Identification strategy

It is important to remember that the data set is created using the quarter 4 of each year as the starting point for each panel, and only household heads are being considered. With that in mind by using the same variable from the socioeconomic and demographic questionnaire of the ENOE, which identifies when a individual leaves the household to migrate, it is possible to identify migrants one period before they take the decision to move. The previous allows us to know all their information for the entire population, migrants or non-migrants, and compare them before migration in the same way as Fernández-Huertas (2011).

One disadvantage of this survey is that it only follows the same individuals and household for 5 quarters, and it is most likely to never get information of a person that leaves once disappears from the data set; nonetheless, it is sufficient to have the person at least once to make the comparison between migrants and non-migrants in Mexico.

Descriptive statistics

The strength of the ENOE data lies in its ability to track the distribution of the population according to their profiles over time. This chapter leverages the richness of the ENOE data to analyze these dynamics. Table 10 provides general descriptive statistics that enable a comparison between migrants and non-migrants, with a focus on the differences between risk-averse and risk-taking individuals. The data includes 9,212 risk-averse migrants compared to 12,211,392 risk-averse non-migrants, while there are 6,831 risk-taking migrants versus 10,769,405 risk-taking non-migrants.

The average age of risk-averse migrants is 41.4 years, which is 7 years younger than their non-migrant counterparts. Overall, non-migrants tend to be older than migrants. In terms of schooling, risk-averse non-migrants have the highest average level of education at 7.01 years, which is still lower than that of non-migrant females. Male migrants in the same category have slightly less schooling compared to non-migrant males. This pattern is similar for risk-takers, with migrants having less schooling than non-migrants. Labor force participation stands at 57.95% for risk-averse migrants, slightly lower than the 60.60% participation rate for risk-taker migrants. Interestingly, labor force participation is higher for risk-takers than risk-averse individuals among migrants. Finally, risk-averse migrants earn the highest average monthly income compared to all other groups.

Source: ENOE, INEGI.

In terms of schooling, migrants who are risk-takers tend to have the lowest average educational attainment. However, this comparison is drawn from the overall population in the dataset. A more detailed, year-by-year analysis of the distributions would provide a deeper understanding of the composition within each group, shedding light on any shifts in educational levels over time and how they may relate to migration decisions. Examining yearly trends can also reveal if specific economic or political events impact the educational profile of migrants.

Figure 11 further breaks down this information for men. Among risk-averse men, those with elementary education are largely employed in the agricultural sector, which suggests that individuals with lower educational levels gravitate towards traditional, labor-intensive industries. On the other hand, college-educated risk-averse men tend to work in the service

Table 9: General Descriptive Statistics

	No mig		Mig	
	RT	RA	RT	RA
Obs	10,769,405	12,211,392	6,831	9,212
%	46.83%	53.10%	0.03%	0.04%
Age				
Mean	48.65	48.59	41.55	41.43
Median	47	47	40	40
Rural	0.3211	0.3584	0.6832	0.6637
Schooling	8.2727	9.1765	7.9838	5.4314
Labor force participation	62.15	92.06	60.60	57.95
Wage earners	42.07	84.62	39.69	57.95
Average Monthly income				
Mean	428.70	5197.39	443.50	3685.20

sector, highlighting how higher education correlates with employment in more diverse and potentially higher-paying industries. For risk-takers, a similar pattern is observed among elementary-educated individuals, with most working in agriculture. However, unlike their risk-averse counterparts, a notable portion of risk-takers with elementary education also find employment in the service sector, indicating that this group may be more willing to transition into different types of employment despite having lower educational qualifications. This diversification of job sectors for risk-takers points to a flexibility in career paths that may be driven by their greater willingness to take risks in an uncertain labor market.

When analyzing the average years of schooling for each group over time, as shown in Figure 8, a clear pattern emerges for risk-averse individuals. Female migrants consistently have fewer years of schooling compared to non-migrant females, and this same trend is observed among males, where migrant men typically have less schooling than their non-migrant counterparts. Interestingly, the gap in educational attainment between migrants and non-migrants is generally narrower for women than for men, suggesting that the educational divide plays a slightly less significant role for women when making migration decisions.

Table 10: Male occupation by sector and educational level

Male migrants - sector of employment by educational level (Risk averters)

	Construction	Manufacturing	Comerce	Services	Others	Agriculture	Not specified	Total
None	10,523	2,047	1,870	2,453	0	20,538	0	37,431
Preschool	0	0	0	0	0	68	0	68
Elementary school	85,001	31,279	15,331	30,276	3,384	133,082	0	298,353
Junior hgihgschool	50,083	31,290	17,821	37,428	1,664	71,648	0	209,934
Highschool	14,148	10,077	7,868	26,344	124	14,479	326	73,366
Postsecundary (teachers school)	292	0	0	189	0	0	210	691
Postsecundary (technical carreer)	516	2,060	728	1,578	0	398	0	5,280
College	2,055	3,636	3,821	9,647	0	1,458	102	20,719
Masters	0	0	0	571	0	86	0	657
PhD	0	0	0	104	0	0	0	104
	162,618	80,389	47,439	108,590	5,172	241,757	638	646,603

Male migrants - sector of employment by educational level (Risk lovers)

	Construction	Manufacturing	Comerce	Servicios	Others	Agrivulture	Not especified	Total
None	694	0	955	0	637	19,004	464	21,754
Elementary school	11,730	7,238	3,320	10,887	0	80,197	29,370	142,742
Junior highschool	7,604	3,006	5,817	10,417	439	25,597	14,968	67,848
Highschool	2,271	3,842	4,199	7,897	57	4,153	10,983	33,402
Postsecundary (teachers school)	0	0	0	382	0	0	257	639
Postsecundary (technical carreer)	125	158	751	1,298	0	200	1,363	3,895
College	757	1,748	4,913	8,452	392	394	2,441	19,097
Masters	36	0	0	3,102	0	0	0	3,138
PhD	0	0	0	66	0	0	0	66

Source: ENOE, INEGI.

In contrast, risk-taker female migrants tend to have more years of schooling than their non-migrant peers, with this difference becoming particularly pronounced in the years 2016 and 2017. This observation suggests that education may play a more critical role in the decision to migrate for risk-taking women, who appear to leverage their higher education for opportunities abroad. The trend for risk-taker male migrants, however, is less consistent. In some years, male migrants in this group exhibit higher levels of schooling than non-migrants, while in other years, they have lower average education. This inconsistency could reflect broader fluctuations in the labor market or shifts in the types of skills that are valued both in Mexico and the U.S., affecting whether higher-educated men are more likely to migrate in certain periods. These variations highlight the complexity of the relationship between risk-taking behavior and educational attainment in shaping migration patterns, particularly across different genders and time periods.

What can be confirmed is that the distribution of migrants and non-migrants evolves over time, influenced by shifts in the broader socio-economic and political contexts of both Mexico and the U.S., as well as the sending countries. These changes create a dynamic scenario where the decision to migrate is not static but constantly shaped by external factors. As economic conditions fluctuate, policies are implemented, and opportunities arise or diminish, the context in which individuals weigh the costs and benefits of migration is continuously being redefined. This results in an environment where the factors influencing migration decisions—such as job prospects, educational opportunities, and socio-political stability—vary greatly over time.

In light of these shifts, it can be inferred that the self-selection patterns of migrants also change. As new challenges and opportunities emerge, different groups of individuals—varying by risk tolerance, education, and skill levels—may choose to migrate, altering the overall profile of the migrant population. For instance, as Jaeger et al. (2010) noted, during periods of uncertainty—resulting from economic crises or political instability—individuals with higher risk tolerance may be more likely to migrate. Conversely, in more stable times, those with secure economic prospects might also consider migration. These contextual changes, when examined in aggregate, suggest that self-selection is not a fixed characteristic but rather one that adapts to the evolving conditions of both the origin and destination countries.

Table 11: Average schooling by gender, risk aversion and migration

Average schooling by gender, risk aversion and migration profile

	Risk averse				Risk lovers			
	Women		Men		women		men	
	Mig	No-mig	Mig	No-mig	Mig	No-mig	Mig	No-mig
2007	7.1091	8.3026	7.1091	8.3026	8.7506	5.7280	7.2157	7.1321
	0.1208	0.0008	0.1208	0.0008	0.0581	0.0016	0.0384	0.0013
2008	7.8720	8.2862	7.8720	8.2862	4.9794	5.9160	5.7099	7.2937
	0.0897	0.0007	0.0897	0.0007	0.0479	0.0014	0.0152	0.0011
2009	5.9321	8.3813	5.9321	8.3813	9.0324	6.2149	7.2762	7.6730
	0.0581	0.0007	0.0581	0.0007	0.1207	0.0014	0.0257	0.0011
2010	5.7261	8.5035	5.7261	8.5035	2.6687	6.3622	7.2107	7.7876
	0.0700	0.0007	0.0700	0.0007	0.0653	0.0015	0.0211	0.0011
2011	7.3281	8.5072	7.3281	8.5072	4.7144	6.4492	6.6369	8.0520
	0.0521	0.0007	0.0521	0.0007	0.0473	0.0015	0.0225	0.0011
2012	7.0792	8.6307	7.0792	8.6307	7.0393	6.6585	6.5745	8.1928
	0.1407	0.0007	0.1407	0.0007	0.1918	0.0015	0.0322	0.0011
2013	9.5058	8.6909	9.5058	8.6909	5.6725	6.7899	8.3904	8.3127
	0.0597	0.0008	0.0597	0.0008	0.0839	0.0017	0.0619	0.0012
2014	4.7865	8.6857	4.7865	8.6857	8.3676	6.8610	6.7274	8.4719
	0.0388	0.0007	0.0388	0.0007	0.0603	0.0014	0.0222	0.0011
2015	8.4054	8.6880	8.4054	8.6880	6.8750	6.9762	7.0327	8.5781
	0.1440	0.0007	0.1440	0.0007	0.0528	0.0013	0.0248	0.0010
2016	6.6300	8.7287	6.6300	8.7287	11.9639	7.1708	9.3681	8.6796
	0.0674	0.0006	0.0674	0.0006	0.2746	0.0013	0.0569	0.0010
2017	11.2818	8.7784	11.2818	8.7784	7.9662	7.4291	7.8423	8.8810
	0.1018	0.0007	0.1018	0.0007	0.0755	0.0013	0.0408	0.0010

Source: ENOE, INEGI.

Results

This section presents empirical evidence on the self-selection of Mexican emigrants, focusing exclusively on individuals surveyed within Mexico who hold Mexican nationality. It is important to note that this analysis does not consider migrants from other countries who either temporarily reside or transit through Mexico. Although it would be both challenging and valuable to include such migrants for a more comprehensive understanding of Mexico's labor market and the overall dynamics of migration, this study limits its scope to Mexican nationals. Expanding the analysis to include foreign migrants would provide deeper insights into the complexities of Mexico's evolving role as both a sending and transit country, but for the purposes of this chapter, only Mexicans are examined.

The first set of results presented will be Kernel density estimations, followed by an analysis of the differences between the Kernel densities. As demonstrated in the previous chapter, this approach has proven to be the most effective way to observe and identify self-selection biases in migration. By focusing on Kernel estimations, this analysis provides a clearer picture of how self-selection patterns have shifted over time. Additionally, the goal is to determine whether there is a specific point in time when these changes in self-selection become particularly pronounced. This method allows for a more nuanced understanding of how external factors, such as economic crises or policy changes, might have influenced the migration decisions of different groups over the years, offering important insights into the evolving profile of Mexican emigrants.

Kernel Estimations

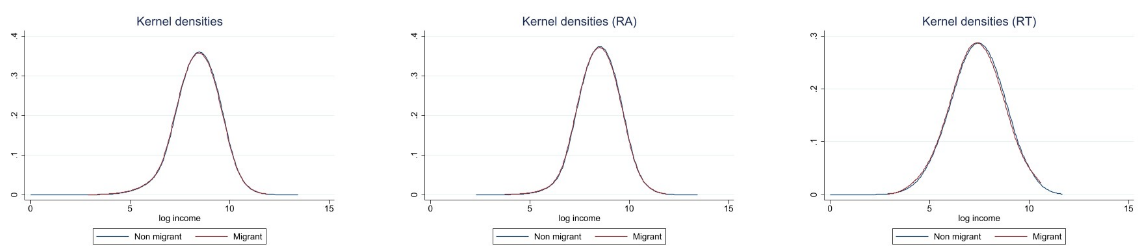
The Kernel density graphs illustrate the log income distributions for migrants and non-migrants, offering insights into the self-selection framework. This framework helps assess whether migrants are positively, negatively, or neutrally selected by comparing the income distributions of both groups, revealing patterns that suggest different selection dynamics.

To present the results and uncover possible selection biases, Kernel density estimations and their corresponding difference plots are used. The analysis proceeds in three steps. First, it examines the full 2007–2017 period, disaggregated by risk aversion profile. Second, it explores changes over time by presenting year-by-year comparisons within each risk group. Finally, the analysis incorporates additional statistical tools to evaluate the role of observable and unobservable characteristics in shaping selection outcomes.

As mentioned, the first set of results corresponds to the pooled period from 2007 to 2017. Figures 16 and 17 show that, when considering the full sample, the selection pattern appears to be slightly negative. However, once the data is disaggregated by risk aversion, a clearer pattern of positive selection emerges for the risk-averse group. These preliminary findings will be further refined and contextualized in the following sections, where a yearly breakdown is provided to capture more nuanced dynamics over time.[15]

Figure 16: Kernel distributions estimation (All)

(a) **(b)** **(c)**



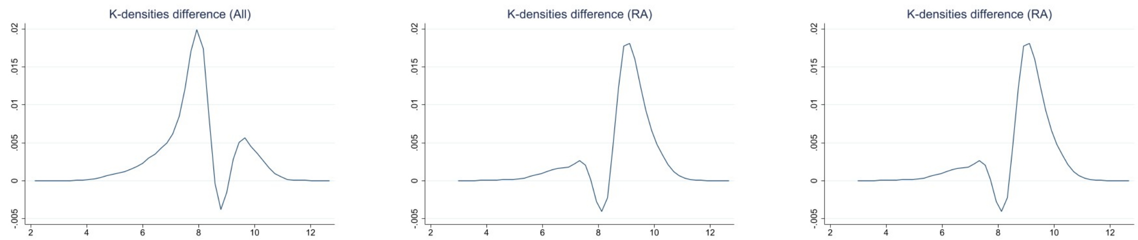
Source: ENOE, INEGI.

In Figure 18, the Kernel density comparisons are presented for the entire population, without disaggregation by risk aversion profile. While in some cases the type of selection may appear visually evident, a more precise identification requires examining the corresponding Kernel density difference plots. These are shown in Figure 19, and they prove especially helpful in distinguishing the nature of the selection bias. For the years 2008, 2009, and 2015, the graphs reveal clear signs of negative selection, as the non-migrant distribution dominates the migrant distribution across most of the income range. In contrast, for 2007, 2010, 2011, 2012, 2013, and 2014, the patterns suggest positive selection, with migrants overrepresented at higher income levels.

[15] It is important to note that Kolmogorov–Smirnov tests were conducted to assess the statistical significance of the observed differences in distributions. For the pooled sample, the null hypothesis of equal distributions between migrants and non-migrants was rejected with a p-value of 0.001, indicating a significant difference in income distributions.

Figure 17: Kernel estimations difference (All)

(a) **(b)** **(c)**



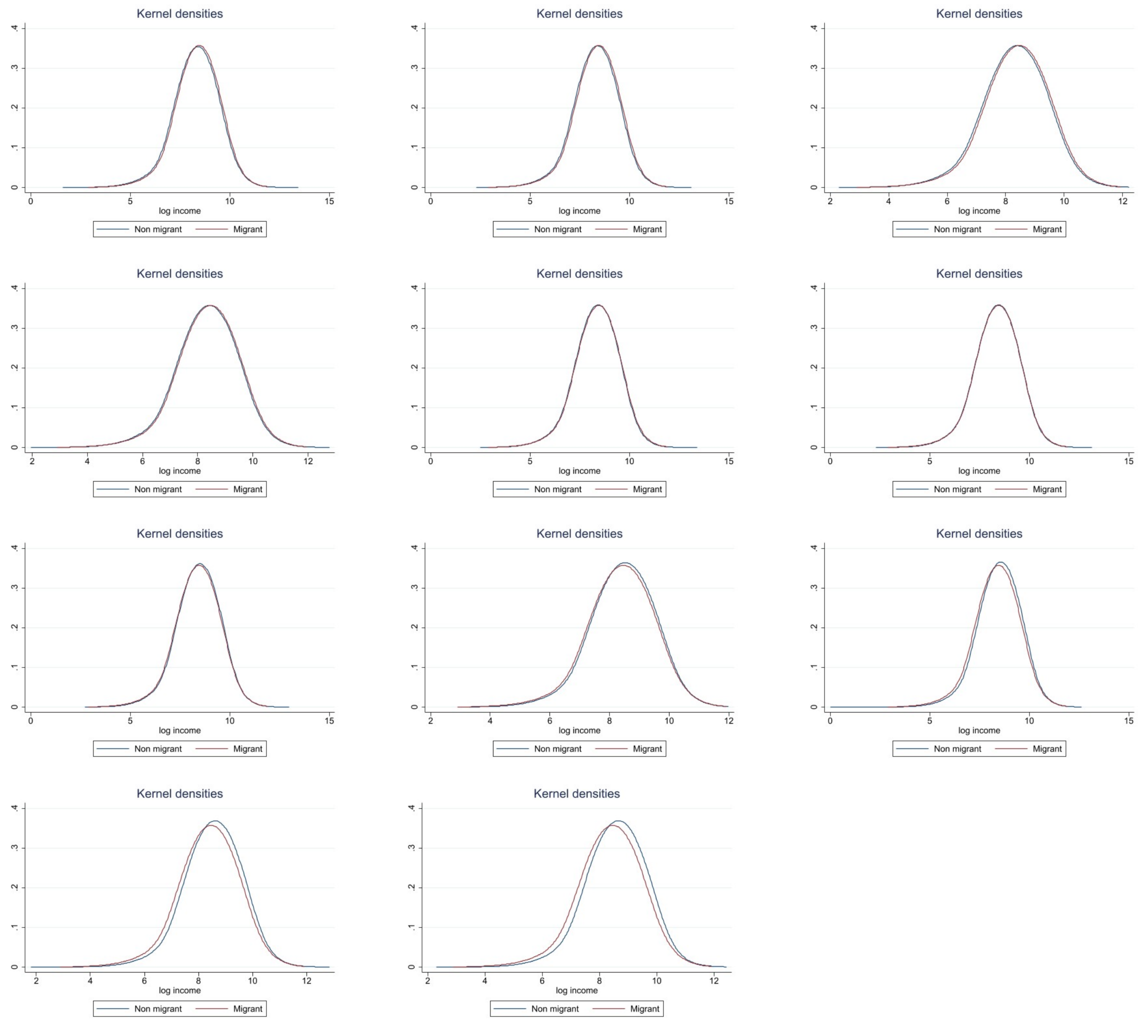
Source: ENOE, INEGI.

In the final years of the period—2016 and 2017—the migrant distribution appears shifted to the right across the entire range, resulting in a consistently positive difference. However, this uniform shift makes it difficult to identify a specific selection pattern based solely on the income distribution. These results underscore the importance of further disaggregating the data by risk aversion profile to gain a clearer understanding of the underlying selection dynamics.

These patterns resonate with prior empirical work. The observed positive selection in several years aligns with the findings of Chiquiar and Hanson (2005), who showed that Mexican migrants are often drawn from the middle and upper segments of the income distribution. Meanwhile, the intermittent presence of negative selection echoes the conclusions of Fernández-Huertas (2011), who, using pre-migration earnings, found that migrants were more likely to come from the lower end of the distribution, especially under certain economic constraints. The shifting patterns across years also support the argument that selection is context-dependent and influenced by broader structural factors—such as wage differentials, labor demand, and policy changes—that affect both the incentives to migrate and the profile of those who do so.

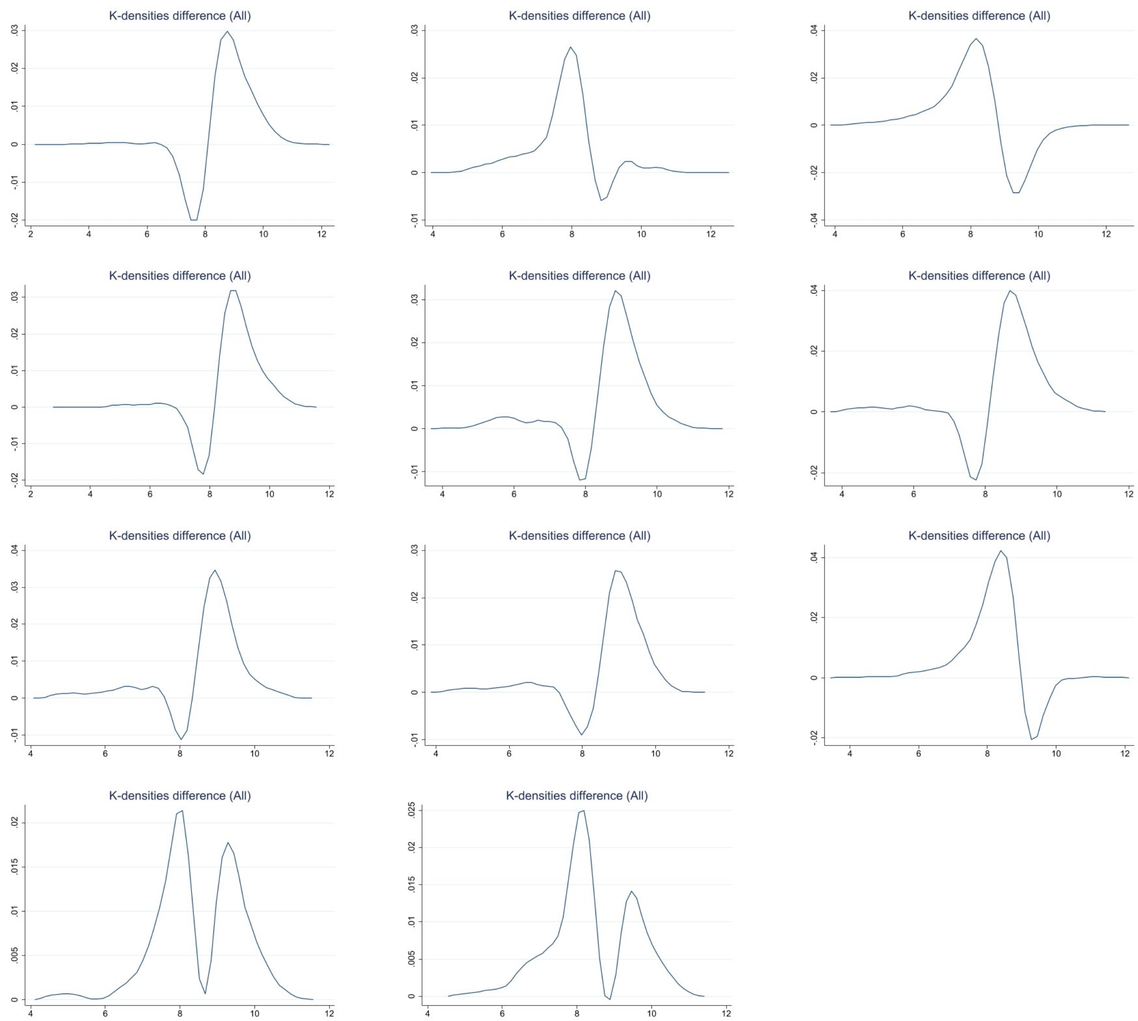
To streamline the presentation and enhance interpretability, only the Kernel density difference graphs are shown in this section. The full set of distribution plots is available upon request. Figure 21 presents the difference in log income distributions between migrants and non-migrants for individuals classified as risk-averse, while Figure 22 displays the corresponding results for risk-takers. This disaggregation by risk preference provides

Figure 18: Kernel estimations - Migrants vs non-migrants



Source: ENOE, INEGI.

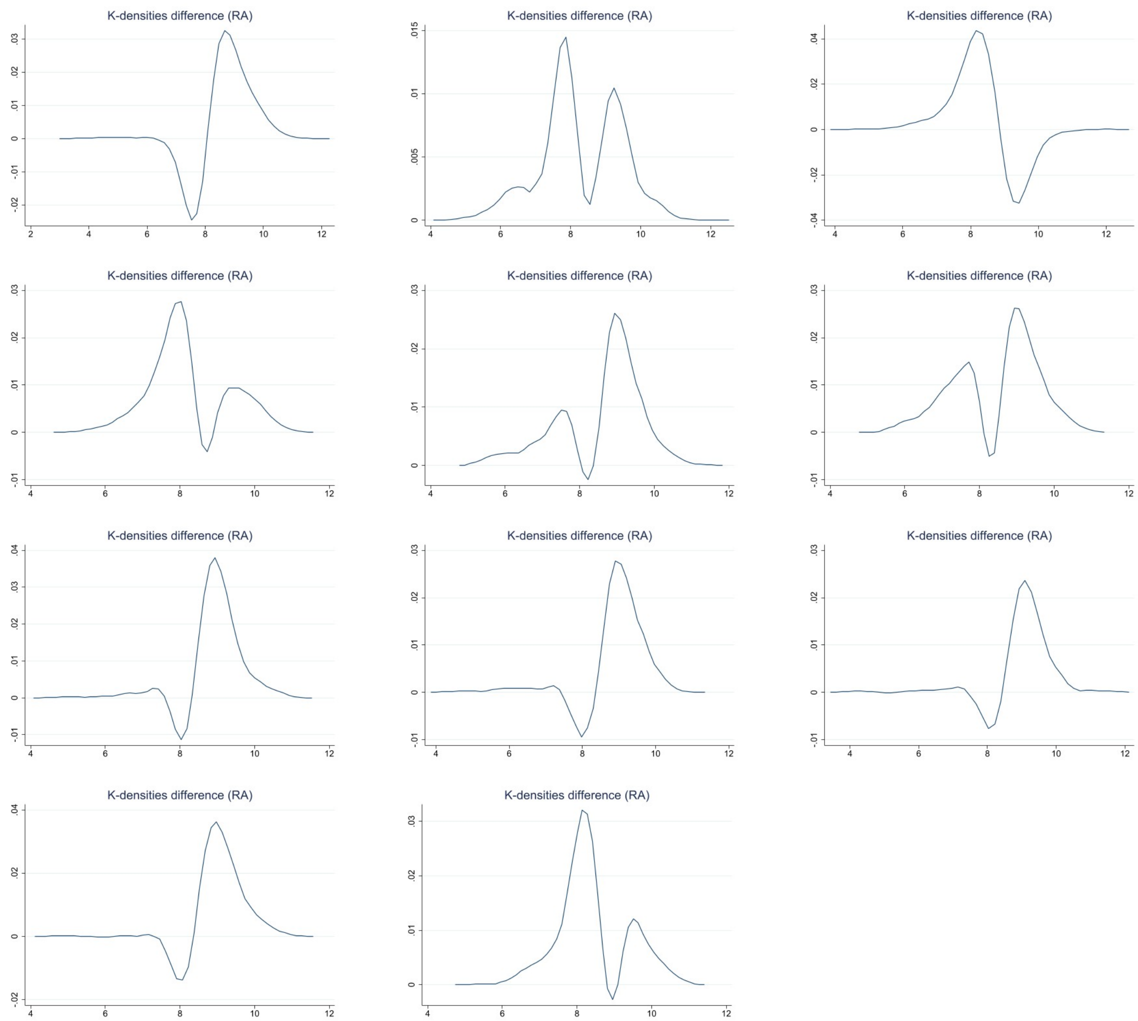
Figure 19: Kernel estimations difference - Migrants vs non-migrants



Source: ENOE, INEGI.

a clearer view of how selection dynamics vary not only over time but also across behavioral profiles, offering a novel lens through which to interpret heterogeneity in migration decisions.

Figure 20: Kernel estimations difference - Migrants vs non-migrants (RA)



Source: ENOE, INEGI.

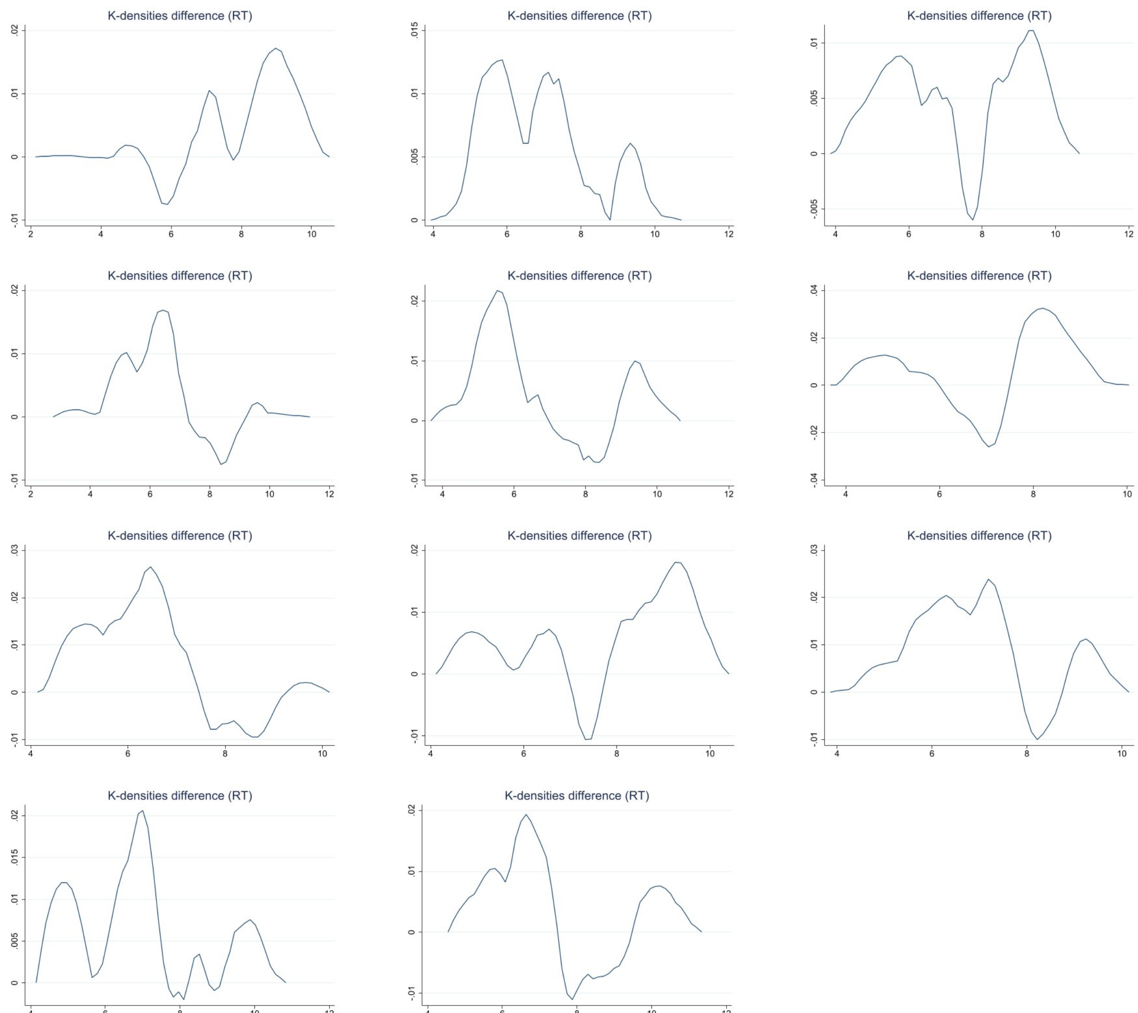
The results for risk-averse individuals, presented in Figure 20, show clear evidence of positive selection in 2007, 2013, 2014, 2015, and 2016, as migrants are overrepresented in the higher segments of the income distribution. In contrast, 2009 displays a clear pattern of negative selection. However, for some years, the patterns are less conclusive. For example, in 2008, the distributional difference lacks a significant negative mass, making it difficult to determine the direction of selection. Similarly, for 2010, 2011, and 2017, no consistent pattern emerges—migrants appear to be drawn from both below and above the income mean, but not from the center. This may suggest a bifurcated selection process, where individuals are self-selecting from the flanks of the distribution rather than the middle. It is also important to note that these ambiguous patterns may partly reflect sample size limitations or noise in the data for these years, especially as the migrant subgroup becomes smaller and more heterogeneous when disaggregated by behavioral profile.

In the case of risk-takers, Figure 21, the results do not allow for definitive conclusions regarding selection patterns across any of the years analyzed. The Kernel density difference graphs fail to reveal a consistent or dominant trend—whether positive, negative, or intermediate—across the income distribution. As previously noted, this ambiguity is likely due to both the limited representation of migrants in the ENOE and the increasing heterogeneity within the risk-taker subgroup when disaggregated by year. The dilution of observations weakens the statistical power of the analysis and increases the likelihood of noise overshadowing any underlying signal.

This challenge is not unique to this study. As Fernández-Huertas (2011) notes, when working with short-panel labor surveys such as ENOE, small sample sizes and the structure of the data can limit the identification of subtle self-selection patterns, particularly in the tails of the distribution. This is especially true when individuals are further segmented by risk preferences or demographic characteristics.

In sum, the results presented so far in this chapter provide a nuanced understanding of migrant self-selection patterns between Mexico and the United States. By leveraging Kernel density estimations and disaggregating by risk preferences, the analysis uncovers important differences in how individuals with varying risk attitudes are represented across income distributions. While overall patterns suggest a mix of positive and negative selection depending on the year, the disaggregation by risk profile reveals more systematic behavior among risk-averse individuals, with clearer episodes of positive selection. In contrast, the patterns for risk-takers remain less conclusive, likely due to sample size constraints and higher heterogeneity in this group.

Figure 21: Kernel estimations difference - Migrants vs non-migrants (RT)



Source: ENOE, INEGI.

These findings contribute to the broader literature by confirming that migration selection is context-dependent and shaped by both structural conditions and individual traits. They offer empirical support for previous studies that have identified both positive and negative selection depending on economic and institutional environments. More importantly, this study advances the conversation by introducing behavioral heterogeneity—specifically risk aversion—as a key explanatory factor in migration dynamics.

Together, these insights suggest that migration decisions cannot be fully understood without considering how individual risk profiles interact with labor market conditions and policy environments. As such, the results underscore the value of incorporating psychological and behavioral dimensions into migration models, offering a more comprehensive lens through which to design evidence-based and inclusive migration policies.

To deepen the analysis, the next section presents results for both observable and unobservable skills, following the same structure as before: first for the overall population and subsequently disaggregated by risk preference. This approach allows for a more comprehensive examination of how unobserved characteristics may contribute to the observed selection patterns. By disentangling the role of measured and unmeasured factors in the migration decision, the analysis aims to provide a more complete understanding of the underlying selection dynamics and the behavioral heterogeneity among migrants.

Observed and unobserved skills.

To obtain the graphs reflecting the influence of observed and unobserved characteristics on selection patterns, a series of linear regressions were estimated over the full 2007–2017 period. The dependent variable is the log of monthly labor income, and the vector of explanatory variables includes indicators for household size (more than one member), marital status, rural origin, years of schooling, age group, whether the individual comes from a historically migrant-sending state, previous employment sector, and gender. Year fixed effects and a risk-aversion profile identifier are also included to control for time trends and behavioral differences. A more detailed specification of the regression model and the variables used is presented in the following section.

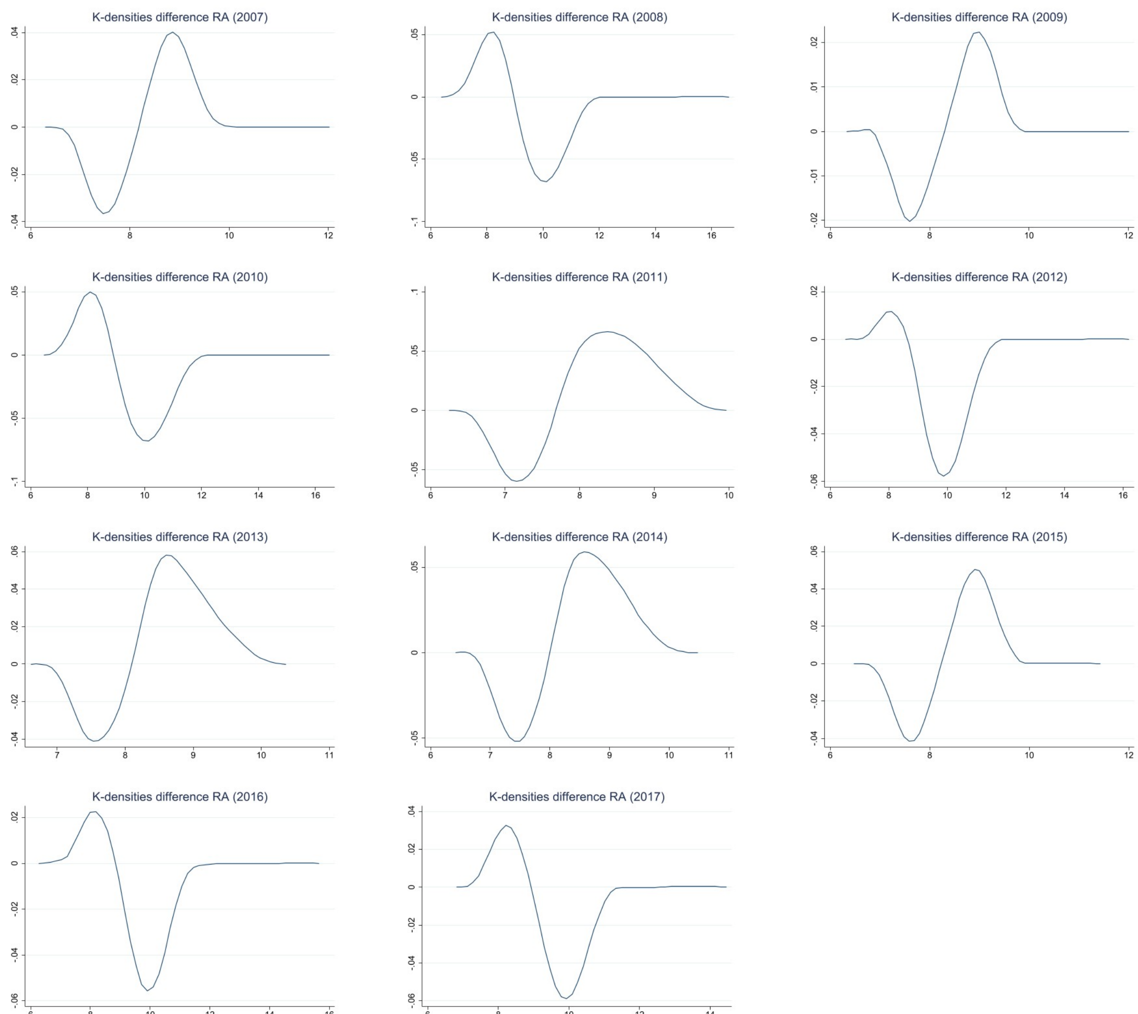
Figure 22 presents the Kernel Kernel difference plots based on observable characteristics for risk-averse individuals. These are followed by Figure 23, which displays the corresponding results for unobservable characteristics, derived from the residuals of the income regressions. As in the previous section, only the Kernel density difference plots are shown in order to streamline the presentation and facilitate interpretation of the selection patterns.

The Kernel density difference plots for observable characteristics among risk-averse individuals reveal a pattern of positive selection in the years 2007, 2009, 2011, 2013, 2014, and 2015. In contrast, the remaining years—2008, 2010, 2012, 2016, and 2017—exhibit signs of negative selection. These shifts may reflect broader structural or cyclical changes in the Mexican labor market and migration context, such as varying wage differentials, economic shocks, or changes in U.S. immigration enforcement. Additionally, they may point to evolving incentives for migration among different segments of the population, with certain years favoring the migration of more skilled individuals and others reflecting a relative increase in the outflow of less-skilled individuals.

The analysis of unobservable characteristics, by contrast, provides a more nuanced and less consistent picture. Only in 2007 and 2017 do the data show a discernible pattern of positive selection. In other years, the residual-based differences are less conclusive, which could indicate the influence of latent or context-specific factors—such as aspirations, psychological traits, or access to informal migration networks—that are not fully captured by standard surveys. These findings resonate with the work of Hendricks (2001) and **Wassink2022<empty citation>**, who emphasize the critical role of unobserved factors like migration networks, trust channels, or destination knowledge in shaping who migrates and under what conditions.

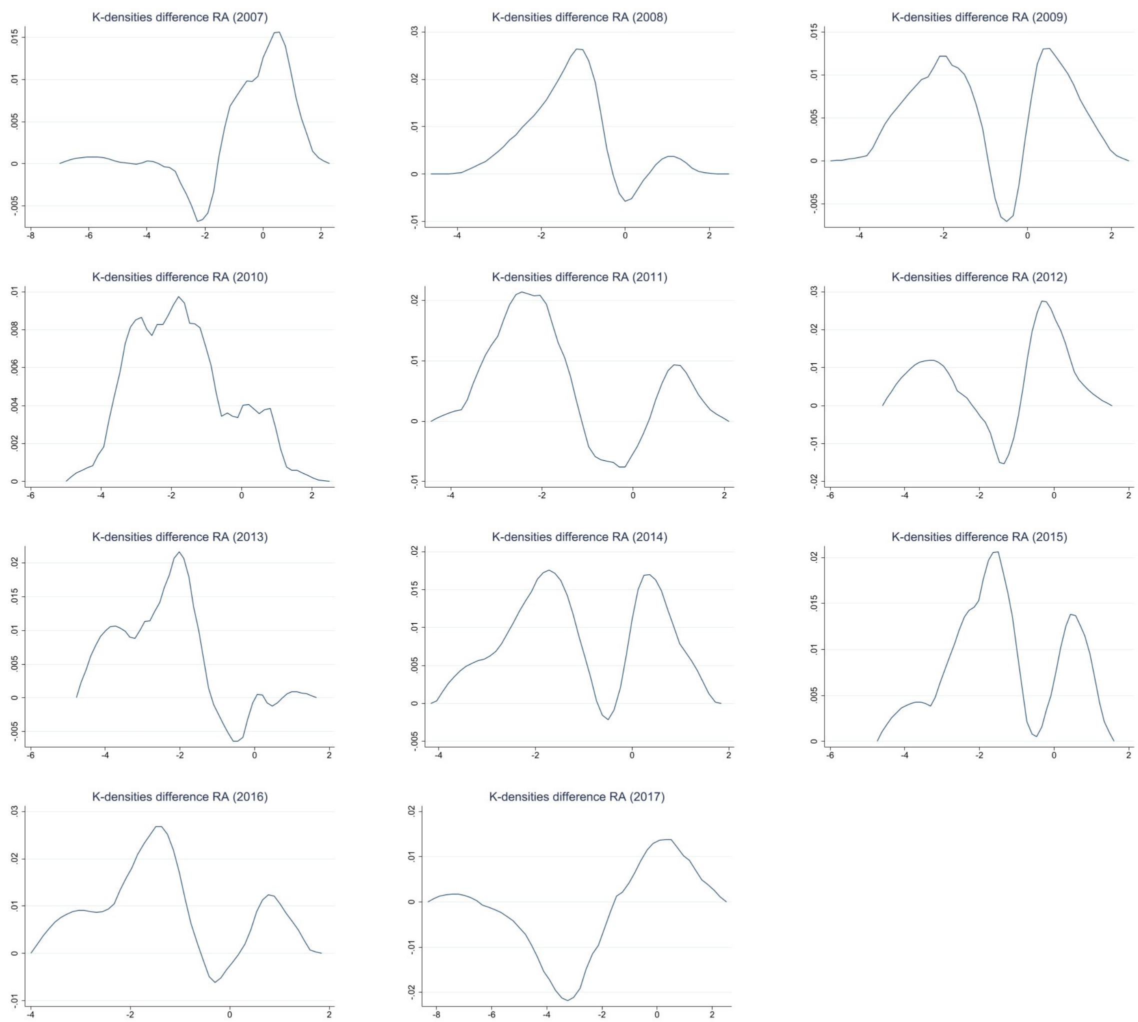
From a policy perspective, these results carry important implications. Since risk-averse migrants respond more predictably to structural incentives, interventions aimed at expanding education access, improving labor conditions, and reducing economic volatility may shape their migration choices. Strengthening public safety and legal migration channels may further reduce uncertainty and discourage unplanned or undocumented migration. Moreover, policies that improve the collection and dissemination of information about migration opportunities, risks, and support systems could help bridge the gap between

Figure 22: Risk-averse Kernel estimations difference for observed skills - Migrants vs non-migrants (2007 - 2017)



Source: ENOE, INEGI.

Figure 23: Risk-averse Kernel estimations difference for unobserved skills - Migrants vs non-migrants (2007 - 2017)



Source: ENOE, INEGI.

observable potential and unobservable uncertainty, making migration decisions more deliberate and better aligned with development goals.

In sum, the analysis highlights the importance of disaggregating migration behavior by both risk preferences and the types of characteristics influencing selection. For risk-averse individuals, observable traits are more systematically associated with migration patterns, while unobservable factors appear less predictive and more sensitive to external shocks or data limitations. Recognizing this distinction is key for designing nuanced migration and development policies. The next section extends this framework to the case of risk-taker individuals, whose decisions may be shaped by a different set of drivers.

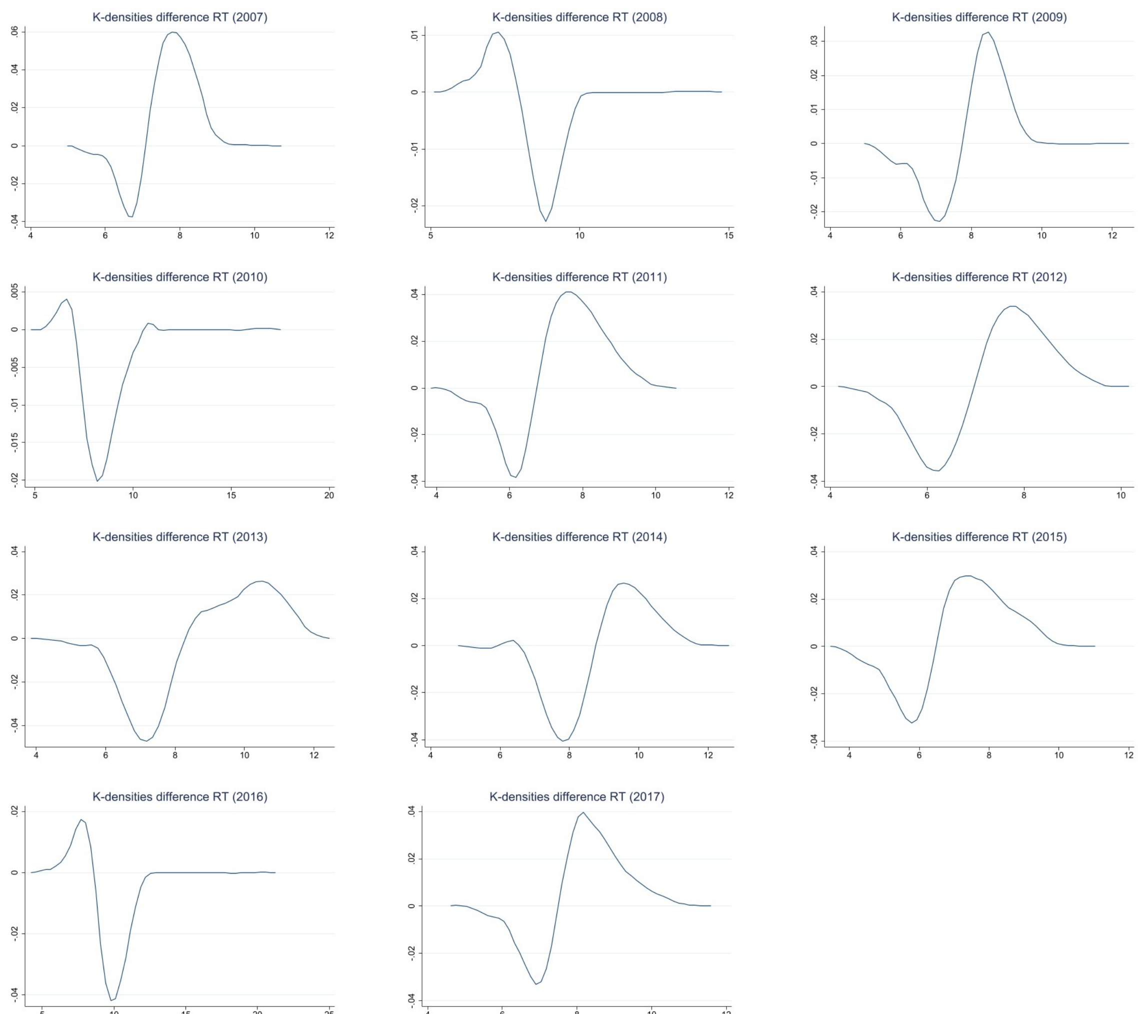
The results for risk-taker individuals based on observable and unobservable characteristics are presented in Figures 24 and 25, respectively. Figure 24 displays the Kernel density difference plots for observable traits between migrants and non-migrants. Evidence of positive selection is apparent in most years—specifically 2007, 2009, 2011, 2012, 2013, 2014, 2015, and 2017—suggesting that, during these periods, migrants were more likely to possess favorable observable attributes such as higher education, employment in certain sectors, etc.. Conversely, negative selection is observed in 2008 and 2016, while 2010 shows no clear pattern, reflecting a more ambiguous selection dynamic for that year.

Figure 25 presents the corresponding results for unobservable characteristics. As in previous cases, the residual-based analysis yields less conclusive results. The graphs do not reveal consistent selection patterns, likely due to sample size limitations and greater heterogeneity within the risk-taker subgroup. This ambiguity reinforces the challenge of detecting selection based on latent traits—such as motivation, aspirations, or access to informal networks—when the underlying data do not fully capture these dimensions.

Taken together, the analysis for risk-takers reveals a more erratic pattern compared to their risk-averse counterparts, suggesting that different mechanisms may be at play in shaping migration decisions across behavioral profiles. These findings underscore the need for further exploration of how risk preferences interact with both observed and unobserved factors to influence migrant self-selection.

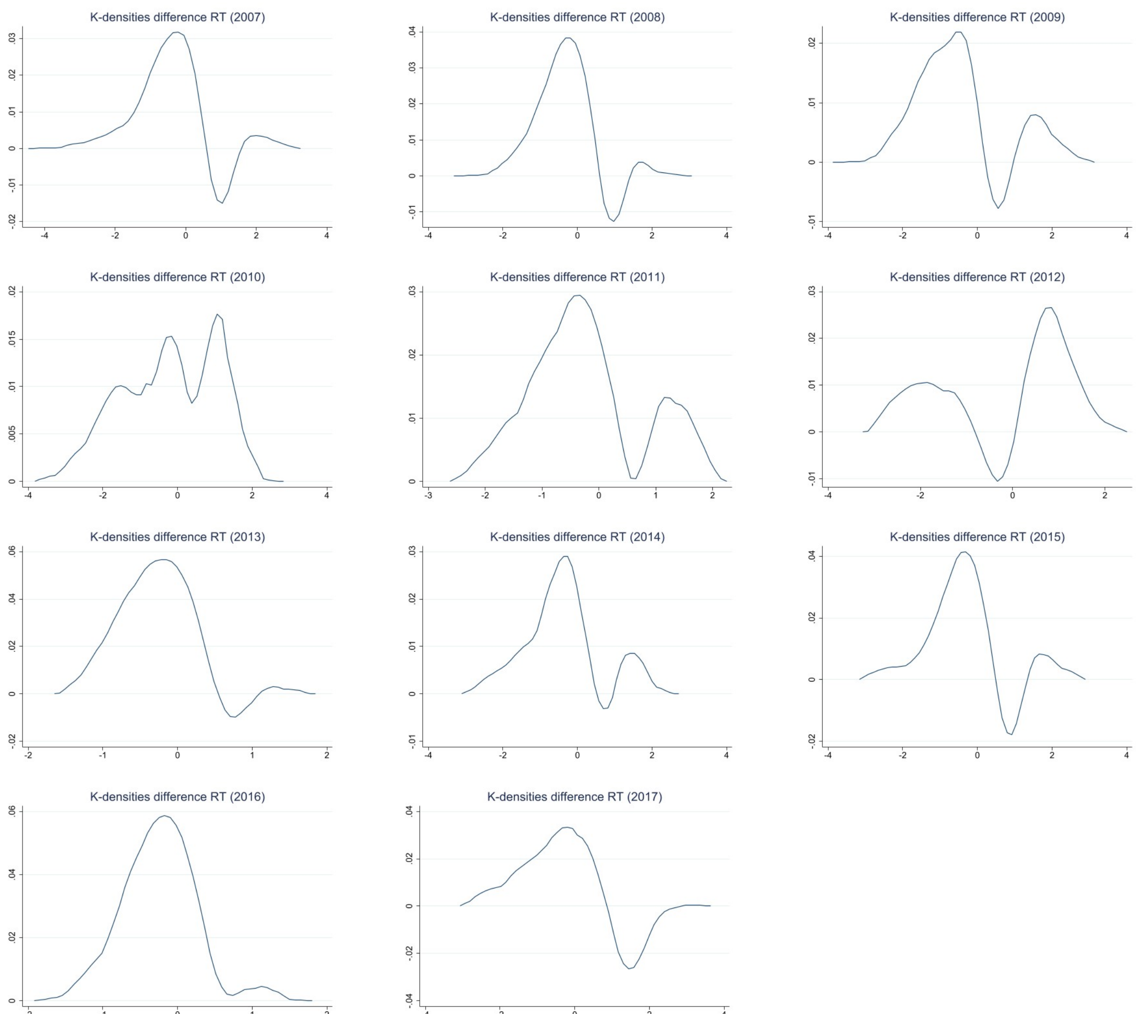
In summary, the analysis of observable characteristics among risk-takers points to recurrent positive selection across several years, suggesting that individuals with favorable socioeconomic profiles were more likely to migrate despite their greater tolerance for

Figure 24: Risk-takers Kernel estimations difference for observed skills - Migrants vs non-migrants (2007 - 2017



Source: ENOE, INEGI.

Figure 25: Risk-takers Kernel estimations difference for unobserved skills - Migrants vs non-migrants (2007 - 2017



Source: ENOE, INEGI.

uncertainty. However, the lack of clear patterns in the unobservable characteristics signals that latent factors may play a less systematic role for this group, or that these factors are more difficult to detect given data limitations. These results indicate that while risk-takers may respond to structural incentives similarly to risk-averse individuals, their migration decisions are potentially influenced by a broader range of motivations and contextual elements. This complexity calls for more nuanced approaches in future research and policy design that account for behavioral heterogeneity within migrant populations.

Taken together, the analysis of observable and unobservable characteristics across both risk-averse and risk-taker groups reveals important distinctions in how different behavioral profiles shape migration self-selection. For risk-averse individuals, observable traits play a consistent and discernible role in migration decisions, whereas unobservable traits display greater ambiguity. In contrast, risk-takers also show signs of positive selection on observable traits in several years, but the influence of unobservable factors remains unclear, likely due to data limitations and the greater behavioral heterogeneity within this group. These patterns suggest that risk aversion moderates how individuals respond to structural incentives and economic conditions, shaping both the strength and direction of selection.

It is important to acknowledge that, due to data limitations, the results could not be disaggregated by gender. Gender-specific analysis would have provided critical insights into how individual characteristics interact with changing contexts that influence migration decisions. Nonetheless, by introducing risk aversion as a distinguishing factor, the analysis highlights clear differences between the groups. This approach offers valuable insights into how risk tolerance shapes migration decision-making and influences the selection bias observed between groups and their skill distributions.

These findings demonstrate that disaggregating based on risk aversion or tolerance provides meaningful insights into the evolving composition of migrant groups, even in the absence of gender-specific data. This approach is crucial not only for deepening our understanding of migration dynamics across countries over time but also for improving how we model risk aversion in such contexts. By integrating a measure of risk aversion, the analysis becomes more precise in capturing how individuals perceive and respond to risk when making migration decisions, thereby contributing to a more comprehensive understanding of migration self-selection.

Regressions

Once we have an idea of when the changes happen, it is necessary to understand where those changes are in terms of the determinants of the income expectations for each of the groups, Migrants and non-migrants, and if there is an effect of time in their decision. For doing the previous, a regression is estimated.

$$ln(income) = \alpha_i + \beta X_i^p + \gamma Y_t^p \epsilon_i + \tau_t \tag{18}$$

Where the vector X is for the sociodemographic variables: Family, Migration state, Married, Rural, Schooling, Age, Economic sector of employment, gender, and risk aversion profile Family represent a dummy variable for belonging a household with a size of at least 2 individuals, Migration state is a dummy variable that represents if the individual comes from one of the 10 states with the highest level of migrants registered in the U.S.[16], Married is a dummy variable for being married; rural is a dummy variable if the person comes from a rural municipality; schooling is a discrete variable for the number of years of formal education: age is a continuous variable; economic sector is a categorical variable for the sector of employment[17]; gender is a dummy variable and risk aversion is a dummy variable for being risk-averse. Y id a vector of dummy variables for each year in the analysis period (2007 - 2017); α is the constant, β the coefficient for the sociodemographic variables, γ the coefficients for the year dummy variables and ϵ and τ the respective error terms. where $t = 2007, ..., 2017$, $p = migrant, non - migrant$

Tables 13 and 14 show the results for non-migrants, where having a family, coming from a rural municipality, having a job in one of the great sectors, and being a woman have a negative effect on the income expectation. The risk aversion variable shifts from a positive and negative effect, depending on the year, and age, schooling, and being married have a positive effect on the income expectations of non-migrants. When we look at the results

[16] The states are: Jalisco, Michoacan de Ocampo, Guanajuato, Veracruz de Ignacio de la Llave, Mexico State, Baja California, Chihuahua, Oaxaca, Guerrero, Puebla, Hidalgo and Sonora. Data from Mexican Census, INEGI.

[17] the sector categories are manufacturing, retail, services, agriculture, and others gather any other productive sector.

for time dummy variables positive and significant effects are presented, when introduced individually and in tandem.

Table 12: Results: regression non-migrants

	log income p/hour												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Family	-0.0456**	-0.0462**	-0.0464**	-0.0461**	-0.0460**	-0.0458**	-0.0456**	-0.0457**	-0.0459**	-0.0461**	-0.0460**	-0.0469**	-0.0500**
	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00147)
Migration state	0.00617**	0.00657**	0.00616**	0.00604**	0.00615**	0.00617**	0.00617**	0.00617**	0.00616**	0.00612**	0.00609**	0.00695**	0.00699**
	(0.000882)	(0.000881)	(0.000882)	(0.000882)	(0.000882)	(0.000882)	(0.000882)	(0.000882)	(0.000882)	(0.000882)	(0.000881)	(0.000880)	(0.000876)
Married	0.0482**	0.0512**	0.0503**	0.0496**	0.0487**	0.0483**	0.0482**	0.0483**	0.0486**	0.0493**	0.0507**	0.0525**	0.0620**
	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00101)	(0.00100)
Rural	-0.181**	-0.182**	-0.181**	-0.181**	-0.181**	-0.181**	-0.181**	-0.181**	-0.181**	-0.181**	-0.182**	-0.181**	-0.182**
	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00135)	(0.00134)
Schooling	0.0451**	0.0450**	0.0448**	0.0451**	0.0451**	0.0451**	0.0451**	0.0451**	0.0451**	0.0450**	0.0449**	0.0448**	0.0441**
	(0.0000899)	(0.0000898)	(0.0000899)	(0.0000898)	(0.0000898)	(0.0000899)	(0.0000899)	(0.0000899)	(0.0000899)	(0.0000898)	(0.0000898)	(0.0000896)	(0.0000893)
Age	0.00348**	0.00341**	0.00345**	0.00345**	0.00346**	0.00348**	0.00348**	0.00348**	0.00348**	0.00346**	0.00342**	0.00334**	0.00312**
	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000416)	(0.0000415)	(0.0000414)
Economic sector													
Manufacturing	-0.182**	-0.182**	-0.182**	-0.182**	-0.182**	-0.182**	-0.182**	-0.182**	-0.182**	-0.182**	-0.182**	-0.182**	-0.183**
	(0.00168)	(0.00168)	(0.00168)	(0.00168)	(0.00168)	(0.00168)	(0.00168)	(0.00168)	(0.00168)	(0.00168)	(0.00168)	(0.00167)	(0.00167)
Retail	-0.317**	-0.317**	-0.317**	-0.317**	-0.317**	-0.317**	-0.317**	-0.317**	-0.317**	-0.317**	-0.316**	-0.315**	-0.311**
	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00170)	(0.00169)
Services	-0.0671**	-0.0662**	-0.0661**	-0.0663**	-0.0667**	-0.0669**	-0.0671**	-0.0671**	-0.0669**	-0.0661**	-0.0654**	-0.0645**	-0.0592**
	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00147)
Other sector	0.197**	0.197**	0.198**	0.197**	0.197**	0.197**	0.197**	0.196**	0.197**	0.198**	0.199**	0.199**	0.205**
	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00386)	(0.00385)	(0.00385)	(0.00383)
Agriculture	-0.633**	-0.633**	-0.632**	-0.632**	-0.632**	-0.633**	-0.633**	-0.633**	-0.633**	-0.632**	-0.632**	-0.632**	-0.628**
	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00194)	(0.00193)
Women	-0.111**	-0.110**	-0.110**	-0.110**	-0.111**	-0.111**	-0.111**	-0.111**	-0.111**	-0.111**	-0.110**	-0.110**	-0.109**
	(0.00130)	(0.00130)	(0.00130)	(0.00130)	(0.00130)	(0.00130)	(0.00130)	(0.00130)	(0.00130)	(0.00130)	(0.00130)	(0.00129)	(0.00129)
Risk averse	-0.00882**	-0.0135**	0.00420	-0.0114**	-0.0105**	-0.00940**	-0.00885**	-0.00879**	-0.00875**	-0.00881**	-0.00857**	-0.00952**	-0.00598*
	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00258)	(0.00257)	(0.00257)
Constant	2.931**	2.949**	2.932**	2.943**	2.940**	2.935**	2.931**	2.930**	2.927**	2.924**	2.921**	2.920**	3.114**
	(0.00362)	(0.00363)	(0.00362)	(0.00363)	(0.00363)	(0.00363)	(0.00363)	(0.00363)	(0.00363)	(0.00362)	(0.00362)	(0.00362)	(0.00387)
Observations	2529865	2529865	2529865	2529865	2529865	2529865	2529865	2529865	2529865	2529865	2529865	2529865	2529865
R-squared	0.223	0.225	0.225	0.224	0.224	0.223	0.223	0.223	0.223	0.224	0.225	0.228	0.235

Standard errors in parentheses
+ .1 * 0.05 ** 0.01
Note: the construction sector is the reference group. In the regression (13) the 2017 dummy omitted because of collinearity.

Table 13: Results: regression non-migrants year dummy vars

	log income p/hour												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
2007		Yes											Yes
2008			Yes										Yes
2009				Yes									Yes
2010					Yes								Yes
2011						Yes							Yes
2012							Yes						Yes
2013								Yes					Yes
2014									Yes				Yes
2015										Yes			Yes
2016											Yes		Yes
2017												Yes	NA

In the case of the regression analysis for migrants, in tables 15 and 16, some variables lose significance over time, yet the overall correlations remain consistent, indicating that the direction of effects—whether positive or negative—remains the same for both migrants and non-migrants. For instance, if a variable has a negative effect for non-migrants, it generally has a similar negative effect for migrants. Despite these shifts, several key factors continue to show significant correlations with migration, typically with a 95% confidence level. These include originating from a migrant state, living in a rural municipality, educational attainment, employment in the secondary or tertiary sectors, being female, and being risk-averse. The continued significance of these variables highlights their persistent influence on the decision to migrate, even as the broader context evolves.

Interestingly, some variables, such as age, gain significance over time. This aligns with the idea that changes in the political, social, and economic contexts modify individuals' economic perceptions, subsequently influencing their migration decisions. As the external environment shifts, individuals may weigh certain factors—like age or employment prospects—more heavily when considering migration. These changes suggest that migration is not a static decision-making process but one that adapts to evolving conditions, with individuals reassessing their priorities and risks based on the current socio-economic landscape. This reinforces the broader notion that determinants of migration, while rooted in personal characteristics and local conditions, are also highly sensitive to the changing context, particularly in terms of economic stability and policy shifts.

Table 14: Results: regression migrants

	log income p/hour												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Family	-0.0910	-0.0791	-0.0945	-0.0912	-0.0890	-0.0914	-0.0907	-0.0908	-0.0905	-0.0914	-0.0894	-0.0846	-0.0752
	(0.0631)	(0.0630)	(0.0631)	(0.0631)	(0.0630)	(0.0631)	(0.0631)	(0.0631)	(0.0631)	(0.0630)	(0.0628)	(0.0629)	(0.0628)
Migration state	0.0790*	0.0795*	0.0797*	0.0789*	0.0785*	0.0781*	0.0790*	0.0790*	0.0782*	0.0786*	0.0761*	0.0795*	0.0756*
	(0.0370)	(0.0369)	(0.0370)	(0.0370)	(0.0370)	(0.0371)	(0.0370)	(0.0370)	(0.0370)	(0.0370)	(0.0369)	(0.0369)	(0.0368)
Married	-0.0283	-0.0185	-0.0284	-0.0292	-0.0289	-0.0288	-0.0286	-0.0288	-0.0277	-0.0268	-0.0278	-0.0180	-0.0103
	(0.0453)	(0.0454)	(0.0453)	(0.0454)	(0.0453)	(0.0454)	(0.0454)	(0.0454)	(0.0453)	(0.0454)	(0.0452)	(0.0454)	(0.0455)
Rural	-0.0856*	-0.0903*	-0.0859*	-0.0850*	-0.0863*	-0.0855*	-0.0855*	-0.0857*	-0.0864*	-0.0879*	-0.0831+	-0.0969*	-0.101*
	(0.0429)	(0.0428)	(0.0429)	(0.0430)	(0.0429)	(0.0429)	(0.0429)	(0.0429)	(0.0429)	(0.0430)	(0.0428)	(0.0430)	(0.0429)
Schooling	0.0585**	0.0572**	0.0574**	0.0585**	0.0586**	0.0585**	0.0584**	0.0585**	0.0581**	0.0583**	0.0570**	0.0576**	0.0540**
	(0.00574)	(0.00574)	(0.00578)	(0.00574)	(0.00574)	(0.00574)	(0.00575)	(0.00574)	(0.00575)	(0.00574)	(0.00574)	(0.00573)	(0.00579)
Age	0.00318	0.00268	0.00320	0.00319	0.00334+	0.00316	0.00318	0.00319	0.00319	0.00307	0.00342+	0.00275	0.00264
	(0.00196)	(0.00196)	(0.00195)	(0.00196)	(0.00196)	(0.00196)	(0.00196)	(0.00196)	(0.00196)	(0.00196)	(0.00195)	(0.00196)	(0.00196)
Economic sector													
Manufacturing	-0.142*	-0.145*	-0.137*	-0.143*	-0.148*	-0.142*	-0.142*	-0.141*	-0.140*	-0.141*	-0.138*	-0.142*	-0.139*
	(0.0621)	(0.0620)	(0.0622)	(0.0622)	(0.0622)	(0.0622)	(0.0622)	(0.0623)	(0.0622)	(0.0621)	(0.0619)	(0.0620)	(0.0621)
Retail	-0.318**	-0.321**	-0.313**	-0.318**	-0.320**	-0.317**	-0.318**	-0.318**	-0.315**	-0.318**	-0.309**	-0.321**	-0.311**
	(0.0730)	(0.0728)	(0.0730)	(0.0730)	(0.0730)	(0.0730)	(0.0730)	(0.0730)	(0.0731)	(0.0730)	(0.0728)	(0.0728)	(0.0727)
Services	-0.0383	-0.0365	-0.0355	-0.0378	-0.0441	-0.0377	-0.0386	-0.0376	-0.0395	-0.0372	-0.0251	-0.0351	-0.0228
	(0.0577)	(0.0576)	(0.0577)	(0.0578)	(0.0578)	(0.0578)	(0.0578)	(0.0579)	(0.0577)	(0.0577)	(0.0577)	(0.0576)	(0.0578)
Other sector	-0.0405	-0.0196	-0.0315	-0.0380	-0.0516	-0.0424	-0.0401	-0.0410	-0.0466	-0.0509	-0.0216	-0.0289	-0.0128
	(0.293)	(0.292)	(0.293)	(0.293)	(0.293)	(0.293)	(0.293)	(0.293)	(0.293)	(0.293)	(0.292)	(0.292)	(0.291)
Agriculture	-0.481**	-0.481**	-0.480**	-0.481**	-0.485**	-0.481**	-0.481**	-0.481**	-0.480**	-0.480**	-0.485**	-0.477**	-0.481**
	(0.0521)	(0.0519)	(0.0521)	(0.0521)	(0.0521)	(0.0521)	(0.0521)	(0.0521)	(0.0521)	(0.0521)	(0.0519)	(0.0520)	(0.0519)
Women	-0.170*	-0.169*	-0.177*	-0.171*	-0.169*	-0.168+	-0.170*	-0.170*	-0.168+	-0.166+	-0.178*	-0.160+	-0.167+
	(0.0856)	(0.0854)	(0.0857)	(0.0857)	(0.0856)	(0.0858)	(0.0857)	(0.0857)	(0.0857)	(0.0857)	(0.0854)	(0.0855)	(0.0855)
Risk averse	-0.290**	-0.291**	-0.271*	-0.289**	-0.293**	-0.291**	-0.290**	-0.291**	-0.285**	-0.292**	-0.290**	-0.290**	-0.275*
	(0.110)	(0.109)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.109)	(0.109)	(0.110)
Constant	3.056**	3.095**	3.058**	3.053**	3.062**	3.061**	3.056**	3.057**	3.048**	3.059**	3.038**	3.054**	3.252**
	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.151)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.164)
Observations	1263	1263	1263	1263	1263	1263	1263	1263	1263	1263	1263	1263	1263
R-squared	0.215	0.220	0.216	0.215	0.216	0.215	0.215	0.215	0.215	0.216	0.221	0.220	0.233

Standard errors in parentheses
+ .1 * 0.05 ** 0.01
Note: the construction sector is the reference group. In the regression (13) the 2017 dummy omitted because of collinearity.

Table 15: Results: regression migrants year dummy vars

	log income p/hour												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
2007		Yes											Yes
2008			No										Yes
2009				No									Yes
2010					No								Yes
2011						No							Yes
2012							No						No
2013								No					Yes
2014									No				No
2015										No			No
2016											Yes		No
2017												Yes	No

Conclusions

This chapter provides a comprehensive examination of migration self-selection patterns from Mexico to the United States between 2007 and 2017. It investigates how economic shocks—such as the 2009 global financial crisis—and political transitions—like the 2012 change in administration in Mexico—affect migrants' selection based on observable and unobservable characteristics. By incorporating risk aversion as a behavioral trait, the analysis extends classical self-selection models (Borjas (1987, 2019)) and provides a more nuanced understanding of how individuals respond to structural conditions and uncertainty.

The findings reveal that self-selection is not static but evolves alongside macroeconomic and political contexts. In line with Chiquiar and Hanson (2005) and Borjas et al. (2018), the analysis shows consistent evidence of positive selection among risk-averse migrants in observable characteristics—particularly in 2007, 2009, 2011, 2013, 2014, and 2015—suggesting that more educated, urban, or otherwise better-positioned individuals are more likely to migrate when faced with uncertainty. Conversely, negative selection in years like 2008, 2010, 2012, and 2016 indicates that economic downturns or changes in perceived returns may lower the threshold for migration among less-skilled individuals.

The results for unobservable traits—proxied through income residuals—are less definitive. For risk-averse individuals, only 2007 and 2017 show clear signs of positive selection, echoing insights from Hendricks (2001) and Wassik and Massey (2022) on the role of migration networks and latent motivations. For risk-takers, while observable characteristics point to positive selection in most years, unobservable traits again lack a consistent pattern, reflecting the heterogeneity and volatility of this group's motivations and constraints. These findings reinforce the notion that risk tolerance is a critical factor shaping how migrants evaluate and act upon opportunities—a dimension often overlooked in canonical models.

In terms of policy implications, these results suggest that interventions should be tailored to behavioral profiles. For risk-averse individuals, policies that reduce uncertainty—such as legal migration pathways, labor market protections, and information access—can have significant effects. Improving local job prospects, formal employment access, and education systems may also reduce the need for migration driven by economic insecurity. For risk-takers, interventions might focus more on network support, community integration, and flexible labor mobility schemes, recognizing that this group is more responsive to informal or aspirational drivers.

Moreover, the dynamic nature of skill selection over time calls for adaptive migration policies. Policymakers in both origin and destination countries must anticipate shifts in migrant profiles by tracking labor demand, wage differentials, and risk-related perceptions. As shown in prior work (Cadena and Kovak (2016) and G. H. Hanson and Liu (2021)), migration is often a response to local labor mismatches and systemic uncertainty; therefore, well-calibrated migration systems can help align human capital flows with labor market needs.

Although the analysis was limited by the inability to disaggregate by gender—an important omission noted in studies such as Aleksynska and Tritah (2014) and Urbanski (2022)—the disaggregation by risk aversion provides an important alternative lens. It illustrates that selection patterns are shaped not just by observable economic indicators but also by deeper behavioral dispositions, underscoring the value of integrating psychological and sociological dimensions into migration research.

In conclusion, this chapter contributes to the literature by bridging the gap between traditional economic models and behavioral approaches to migration. It underscores the need for future research and policy to recognize the heterogeneity of migrants—not only in terms of skills and demographics but also in how they perceive and manage risk. Doing so will help improve the effectiveness, equity, and responsiveness of migration governance in an era of growing economic and social volatility.

Chapter III. Fiscal Costs and Benefits from Mexican Migrants in the Social Security & Welfare System of the U.S..

Abstract

This chapter explores the fiscal effects of Mexican migrants on the U.S. social security and welfare systems over the period 2007 to 2017. Drawing a detailed analysis of the net fiscal balance of Mexican migrants compared to U.S. citizens and other migrant groups. Using data from the Current Population Survey and the Congressional Budget Office, the research examines tax contributions and welfare benefits across different migrant statuses. The findings suggest that while Mexican migrants contribute significantly to the fiscal system through payroll and income taxes, their access to social benefits is generally limited by legal status, impacting the overall fiscal balance. The chapter emphasizes the dynamic nature of fiscal impacts and suggests that policy frameworks should consider these complexities to better integrate migrants into formal labor markets, enhancing their contributions, and mitigating fiscal deficits.

Key concepts: migration; fiscal impact; welfare state; Mexico-U.S..
JEL classification: J61, H20.

Introduction

Migration research can be separated into two areas driven by two main concerns: What is the composition and distribution of migrant groups? And what are the effects that migration has on both the receiving and the sending countries? This research focuses on the latter, aiming to understand the fiscal implications of Mexican migrants in the U.S., particularly through their impact on the social security system. The economic and fiscal implications of migration, especially concerning Mexican-origin populations, are complex and multifaceted, interacting with U.S. local and national fiscal policies, labor markets, and social welfare systems.

Mexican immigrants in the U.S. face distinct vulnerabilities due to their lower income, fewer benefits, and disparities in health insurance access, especially as they approach retirement age. Aguila et al. (2020) highlight that Mexican immigrants often delay retirement to maximize social security benefits, a consequence of their limited participation in employer-sponsored retirement plans. This situation arises from their concentration in low-wage jobs, making them particularly dependent on social security as their primary source of retirement income. The research emphasizes the potential of policy reforms, such as a U.S.-Mexico totalization agreement, to enhance retirement readiness for this vulnerable group.

Borjas (2019) provides further insight into the divergent fiscal impacts of high- and low-skill immigrants in the U.S., showing that high-skill immigrants contribute positively to fiscal balances, with long-term benefits ranging between \$236,000 and \$547,000 per immigrant. In contrast, low-skill immigrants often pose a fiscal burden, with costs ranging from -\$196,000 to -\$301,000 per immigrant, underscoring the importance of targeting high-skill immigration to bolster economic growth. Similarly, Borjas and Tienda (1987) examine the fiscal impacts of immigration and note that while recent Hispanic immigrants often face higher poverty rates and rely on welfare, their strong labor force participation mitigates some fiscal pressure. These findings suggest that immigration policies prioritizing high-skill labor migration could shift the fiscal outcomes more favorably for the U.S. economy.

Boubtane et al. (2016) further explore the relationship between immigration and economic growth in OECD countries, demonstrating that immigration positively affects GDP per capita by increasing human capital. Countries benefit even if they have non-selective migration policies, as immigrants contribute more human capital than any potential dilution effect caused by population growth. This argument is supported by B. Chiswick (1992), who found that immigration has a limited overall effect on wages and employment in the U.S. due to the integration of labor and capital markets, advocating for policies that attract more skilled immigrants to enhance fiscal benefits. Wassik and Massey (2022) analyzes how shifts in migration patterns are influenced by evolving legal frameworks and changes in social and human capital associated with different types of migration. that can induce a more solid participation of foreign-born individuals in the U.S. in the legal labor market and a more intense participation in the tax collection system to decrease the pressure over public expenditures and reach a sustainable fiscal balance.

In order to understand the way that the welfare and social security system can be affected, it is important to understand the dynamics that can hinder the performance of the public finances. Borjas (1998) focus the research on whether the residential choices made by immigrants in the U.S. are influenced by the interstate dispersion in benefits, finding that generous welfare benefits offered by some states have magnetic effects and alter the geographic sorting of immigrants in the U.S., as the migration decision is guided by an income maximization behavior given that they already decide to face the fixed costs of migration, then it is more rational to cluster where the welfare benefits are higher. In a more theoretical approach, Geide-Stevenson and Ho (2004) develop a two-country overlapping generations model to examine the effects of international labor migration in the context of different social security systems. Finding that migration can lead to temporary welfare losses in both the originating and destination countries during the transition period, contrary to the permanent state analysis, which often predicts gains for the destination country. This occurs as the labor market adjusts to the new equilibrium, affecting wages, employment, and the return on capital. With opposite results Ferwerda et al. (2023) present a study that examines this dynamic in the context of Switzerland, finding that despite the significant variation in the welfare offerings in Swiss municipalities and the relatively low barriers to internal movement, the expected patterns of welfare-driven migration are not observed. Therefore, there are no significant effects on local and regional welfare policies.

Clemens (2022) challenges traditional fiscal assessments of immigration, arguing that common cash-flow accounting methods overlook the substantial contributions from capital income generated by immigrant labor. By incorporating conservative estimates of capital taxes paid by employers of immigrant labor, Clemens demonstrates that even low-skill immigrants, often perceived as a fiscal drain, can contribute positively, with adjusted estimates showing a net present value benefit of $128,000 per immigrant. Colas and Sachs (2020) similarly highlight the indirect fiscal benefits of low-skilled immigration. They argue that low-skilled immigrants may lower wages for similarly skilled native workers but increase wages for higher-skilled natives, thereby generating additional tax revenues. This indirect fiscal benefit counters traditional narratives that low-skilled immigrants are a fiscal burden.

Dustmann and Fratinni (2014) in the UK further supports the positive contributions of immigrants to public finances. They find that immigrants from the European Economic Area (EEA) consistently made positive fiscal contributions, particularly immigrants who arrived after 2000, whose education costs were borne by their home countries, thus saving the UK billions. Dustmann et al. (2010) corroborate this finding with evidence that low-skilled migrants from the A8 countries contributed more in taxes than they received in benefits.

From a global perspective, Geide-Stevenson and Ho (2004) explore the fiscal implications of international labor migration in countries with contrasting social security systems. Their findings suggest that migration can initially cause welfare losses during transitional periods, but stabilizes social security systems in the long run. These results align with Lee and Miller (2000) analysis of the U.S., which found that immigrants, while initially a fiscal burden due to their lower earnings and higher public service usage, contribute positively after 16 years. Immigrants help fund public goods and reduce the fiscal strain on native taxpayers, particularly by contributing to the social security system.

Magni (2022) provides an interesting look at how immigrants' economic contributions impact public attitudes toward welfare systems in the U.S., UK, France, and Italy. Despite immigrants' fiscal contributions, they face welfare penalties due to discriminatory attitudes that see them as fiscal burdens. These attitudes persist despite the evidence of immigrants' contributions to local economies, as seen in the study of Mayda et al. (2023), which examines the fiscal impact of immigrants on U.S. local government finances. Their findings show that while low-skilled immigrants can reduce per capita public spending, high-skilled immigrants tend to increase local revenues, enhancing public services.

Access to healthcare for undocumented Mexican immigrants is another significant issue. Vu (2023) underscores the critical role undocumented immigrants play in the U.S. economy, especially during the COVID-19 pandemic, and advocates for the adoption of Canada's ACHIEVE program to improve healthcare access for these vulnerable workers. Vilar-Compte and Gaitán-Rossi (2022) expand on this by illustrating the pre-existing social determinants of health, such as overcrowded housing and limited access to healthcare, which increased the vulnerability of Mexican immigrants during the pandemic. Furthermore, Simula and Trannoy (2018) discuss how high-skilled migration can undermine the progressiveness of tax systems. Skilled workers, who are highly mobile, tend to move to countries with lower tax rates, leading to a "race to the bottom" in taxation that weakens the redistributive effects of progressive taxation systems. Sand and Razin (2006) also explore how immigration can influence the sustainability of social security systems, showing that immigration, particularly of younger workers, can help offset the fiscal burden of the aging population by increasing the ratio of workers to retirees. Finally, Storesletten (2000) proposes that selective immigration policies could replace the need for tax hikes by admitting high - and medium-skilled immigrants, which would generate significant fiscal benefits.

In conclusion, there is a vast literature that addresses in different ways the implications of immigrants in the fiscal, social security, and welfare system of the host country, particularly for Mexico, this topic remains important given the migration dynamics and the flow of people migrating to the U.S.. Then it is relevant to assess the effect of Mexican migrants on the fiscal, social security and welfare system of the U.S.. For this, I will follow the methodology presented in Dustmann et al. (2010) in which the authors evaluated the fiscal consequences of migration to the UK from Central and Eastern European countries, providing detailed insights into the fiscal impact of A8 migrants [18] finding that migrants contribute significantly more to the UK tax and social benefit systems than they receive. This is driven by their characteristics: they are generally younger, better educated, and

[18] Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia.

have fewer children compared to the native population, and access to the benefits system is available to individuals when they reach one year of residence.

These findings can serve as a comparative basis for examining how similar dynamics could play out with Mexican migrants in the U.S., especially considering differences in migrants' age profiles, education levels, and family sizes, which significantly influence their fiscal impacts. This article serves as a guide for this research due to its simplicity and clarity on how to identify the outlays and tax collection. To run the exercise, I will use CPS data and historical data from the Congressional Budget Office.

In the context of this research it is important to understand that most of the migration to the U.S. is illegal, and this phenomenon follows its own dynamic in terms of permanence and access to the benefits system, but for the families that decide to remain in the country and reallocate permanently, the probability of increasing the size of the household is significant by familiar reunion or just by starting a family, then the rest of the family or household member are more likely to have access to some social security or welfare benefit. Therefore, at a household level there will be beneficiaries of the whole social security system and will increase the public expenditure, having an effect on the net fiscal balance. (Borjas in 1995 in the article "The economic benefits of immigration" started to highlight that the economic and fiscal anxieties commonly associated with immigration in the U.S. are largely unfounded. Immigrants provide a substantial net benefit, while there may be costs related to job competition and earnings stagnation, especially among low-skilled native non-migrant workers, these are relatively small. (Colas & Sachs, 2020) reinforce the previous notion and even found that low-skilled immigrants indirectly benefit public finances significantly; their research quantifies these benefits to range between \$770 and \$2,100 dlls annually per immigrant. These benefits primarily stem from changes in wage distributions and tax contributions between different skill levels, where increased wages for high-skilled natives lead to higher tax revenues which can offset the lower taxes collected from lower-wage, low-skilled workers.

Based on the previous and to have a more precise understanding of how the fiscal system is composed and the net fiscal balance is calculated for legal immigrants, illegal migration status migrants, and U.S.-born citizens, four types of government benefits and services need to be considered: direct benefits such as Social Security, Medicare, unemployment insurance, and workmen's compensation; welfare benefits for the poor and low-income population (Medicaid, Food Stamps, the refundable earned income tax credit, public housing, Supplemental Security Income and Temporary Assistance to Needy Families; Public education; and the last public goods. In this analysis, I am only going to focus on two dimensions of benefits, direct benefits and welfare benefits. Also, it is important to understand that migrants contribute to the fiscal system primarily through income, payroll, and consumption taxes, in this research because of the characteristics of the groups only income and payroll taxes are going to be considered.

The chapter will be structured in the following way: first, context changes and literature review; second, methodology and data and identification strategy; third, descriptive statistics and results; finally, conclusions.

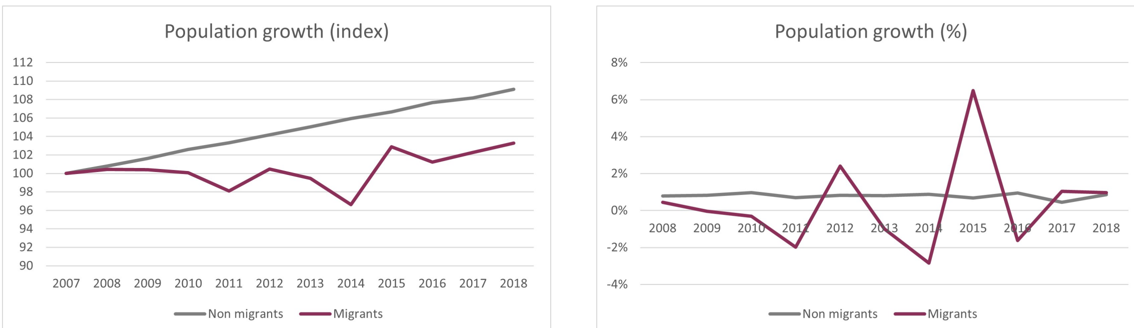
Demographic and fiscal changes over time

Following the idea that self-selection bias changes over time, it is plausible that the effect that individuals have in the economy creates the same sort of changes, not only in the labor market and the wage structure but also in the fiscal system of the host country, in this case the U.S.. The previous is the motivation for this chapter, and as I mentioned before, the second aspect of migration studies in an economic migration framework focuses on the effects on the public sector policies and budgetary provisions and balances.

In particular, if we have in mind the simplest model of low-skill and high-skill effect on taxation, we can infer, as Colas and Sachs (2020) presented, that the effects of immigrants in the labor market can create a positive effect in terms of the indirect costs; therefore, it becomes relevant to assess how the variation of skills distributions can affect the dynamics within the fiscal system; in this case, I will focus on a direct effect assessment. Changes come from different sources: on the one hand, there are changes in the way policies are defined, introduce changes in the definition of policies within the social security system, more open, and sum the changes provided in the historical summary in the SSA stats supplement; on the other hand, there are changes in the composition of migration and how the local labor markets are receiving those new participants.

One of the first things to consider is the volume of migrants and the population growth dynamics, if we are going to analyze the effects on the fiscal impact; in Figure 26, on the left graph, it is possible to observe how the population in the U.S. grows linearly; in the case of migrants, there is also an increasing trend, but there are fluctuations that could be related to many factors, mainly migratory policy and the host and sending country contexts. The previous is clearer in the right-hand side graph from Figure 32, where we can observe the difference in variation rates according to the index that represents the population dynamics.

Figure 26: Population growth dynamics

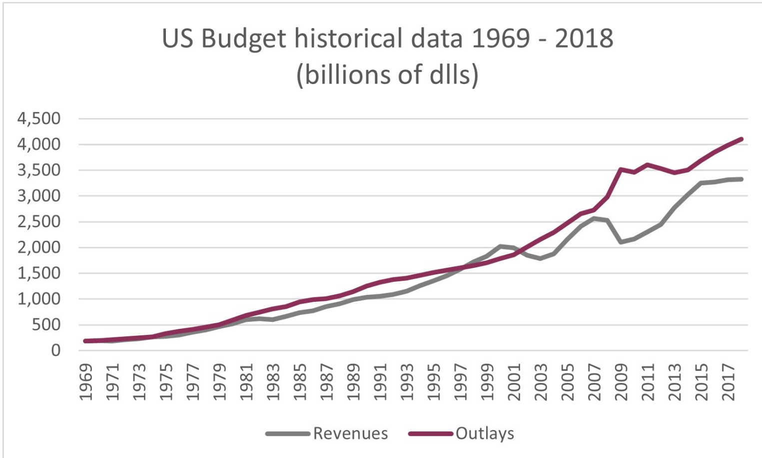


Source: generated with data from the Current Population Survey

As it can be seen in Figure 27, the balance between outlays and revenues started to separate in 2007, generating a general deficit, and the previous also summed up to the pressure of assessing the effect of immigrants on public expenditure in the U.S.. But it is also important to consider that in the overall budget there are also the expenditures of the other two dimensions presented before, public goods and education.

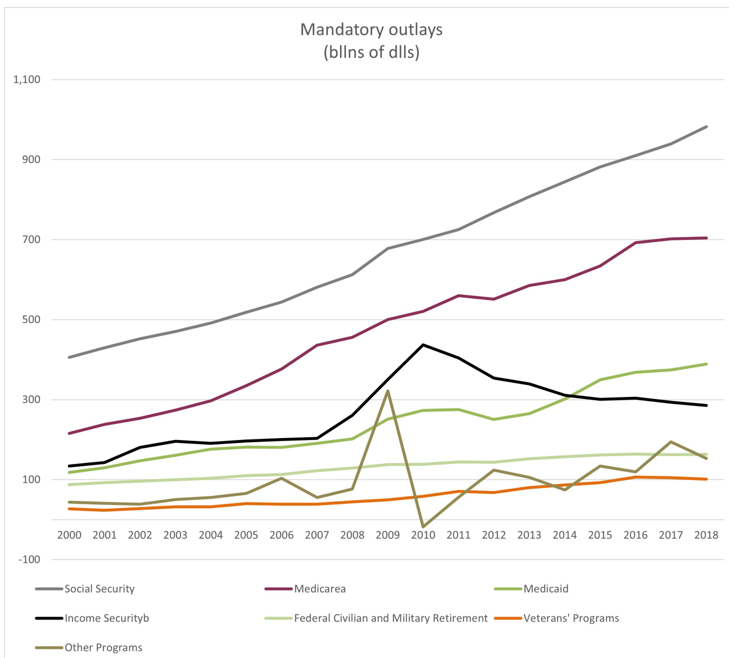
In the same way as population grows and fluctuates, as shown in Figure 28, the dynamics of the public finances in terms of assistance outlays keep an average growth in the same period, 2007 - 2018, where the three main components, as appears in Table 16: social security, Medicare and Medicaid, and the veterans program grew at an average rate over the 5%, that also in terms of magnitude those three are the biggest concepts within the fiscal assistance system. In Figure 28, there is a clear picture of the three most important concepts for mandatory expenditures, social security programs, Medicare and Medicaid, and the federal civilian and military retirement program.

Figure 27: Budget evolution



Source: generated with data from the Budget Congressional Office

Figure 28: Mandatory outlays evolution in time 2000 - 2018



Source: generated with data from the Budget Congressional Office

Table 16: Summary statistics

	Social Security	Medicare[a]	Medicaid	Income Security[b]	Federal Civilian and Military Retirement	Veterans' Programs	Other Programs
2001	5.7%	10.1%	9.7%	6.9%	5.6%	-13.7%	-5.7%
2002	5.3%	6.7%	14.0%	26.0%	3.6%	19.3%	-5.7%
2003	4.1%	8.1%	8.9%	8.8%	3.9%	14.7%	29.2%
2004	4.5%	8.3%	9.7%	-2.8%	3.8%	-0.3%	10.5%
2005	5.5%	12.8%	3.1%	3.3%	5.9%	26.6%	18.1%
2006	4.9%	12.4%	-0.6%	1.6%	3.1%	-5.0%	57.5%
2007	6.9%	15.7%	5.5%	1.5%	8.2%	0.2%	-46.0%
2008	5.3%	4.6%	5.7%	28.3%	5.3%	15.9%	37.6%
2009	10.7%	9.6%	24.6%	34.4%	6.8%	11.4%	319.3%
2010	3.4%	4.1%	8.7%	24.9%	0.5%	17.5%	-105.5%
2011	3.4%	7.5%	0.8%	-7.6%	4.2%	21.9%	-416.0%
2012	5.9%	-1.5%	-8.9%	-12.5%	-0.4%	-4.3%	121.4%
2013	5.2%	6.2%	5.9%	-4.0%	6.3%	18.2%	-15.1%
2014	4.6%	2.5%	13.6%	-8.4%	3.3%	7.9%	-29.4%
2015	4.4%	5.7%	16.0%	-3.2%	2.5%	6.5%	80.2%
2016	3.2%	9.2%	5.3%	0.9%	1.4%	15.2%	-10.8%
2017	3.2%	1.4%	1.7%	-3.3%	-0.8%	-1.4%	62.6%
2018	4.6%	0.3%	3.9%	-2.9%	0.3%	-3.5%	-21.3%
Average % growth (2008 - 2017)	**5.1%**	**5.9%**	**7.2%**	**4.6%**	**3.4%**	**9.9%**	**-0.2%**

a. Excludes offsetting receipts.

b. Includes unemployment compensation, Supplemental Security Income, the refundable portion of the earned income and child tax credits, the Supplemental Nutrition Assistance Program, family support, child nutrition, and foster care.

c. Consists of outlays for Medicare (net of premiums and other offsetting receipts), Medicaid, and the Children's Health Insurance Program, as well as outlays to subsidize health insurance purchased through the marketplaces established under the Affordable Care Act and related spending.

Methodology

To accurately estimate the fiscal impact of migrants, it is essential to first understand how the U.S. social security and welfare systems are structured, and how access varies based on citizenship and residency status. This understanding is key to constructing reliable proxies for public costs and benefits. The objective of this analysis is to evaluate the *net direct fiscal contribution* of migrants to the U.S. social security and welfare system. By doing so, the study aims not only to refine the analytical framework but also to offer deeper insight into how institutional access and demographic profiles shape migration decisions and their long-term fiscal implications.

An important consideration is that undocumented migrants in the U.S. typically do not have access to social security benefits, as they lack the legal documentation—specifically a Social Security number—required to participate. Nonetheless, under specific circumstances, they may indirectly benefit through household members who are eligible. Table 17 summarizes benefit eligibility by citizenship and residency status.

Table 17: Benefits access by citizenship and residency status

	People With Permanent Legal Status	People With Temporary Legal Status	People Without Legal Status
Eligible for Social Security	Yes	Yes	Generally, no
Eligible for Medicare	Generally, yes	Generally, yes	Generally, no
Eligible for Medicaid or the Children's Health Insurance Program	Yes, but generally with a delay	Generally, no	Generally, no
Eligible for Refundable Tax Credits	Yes	Yes, but generally with a delay	Generally, no
Eligible for the Supplemental Nutrition Assistance Program (SNAP)	Yes, but generally with a delay	Generally, no	Generally, no
Eligible for Subsidies Through the Health Insurance Marketplaces	Yes	Yes	Generally, no
Eligible for Supplemental Security Income	Yes, but generally with a delay	Generally, no	Generally, no
Eligible for Unemployment Insurance	Yes	Yes	Generally, no
Eligible for Child Nutrition Programs	Yes	Yes	Yes
Eligible for Pell Grants and Student Loans	Yes	Generally, no	Generally, no

To assess the fiscal effect of migrants, the analysis adopts two complementary approaches. Each approach draws from different datasets and levels of aggregation to estimate both the revenues generated and the public expenditures incurred by migrant and non-migrant populations.

First Approach: Micro-Level Estimation Using CPS Data

This approach uses individual-level data from the *Current Population Survey (CPS)*, which allows for the identification of migrants based on nationality, and includes detailed information on labor income, non-labor income (such as transfers), taxes paid, and receipt of government benefits.

The net fiscal balance is calculated by aggregating, across individuals, the total revenue contributed and the total value of public benefits received. The equation is represented as:

$$FB_N = FB_M \Rightarrow \sum_{n=1}^{N} Rev_n - \sum_{n=1}^{N} SS_n = \sum_{m=1}^{M} Rev_m - \sum_{m=1}^{M} SS_m \qquad (19)$$

Where:

- FB_N and FB_M denote the net fiscal balances for non-migrants and migrants, respectively.
- Rev_n includes estimated tax payments (federal income tax, payroll tax, and other state/local taxes) made by non-migrant individual n.
- SS_n includes the estimated monetary value of public benefits received by individual n, such as SNAP, Medicaid, TANF, and housing assistance.
- Rev_m and SS_m represent the same quantities for migrant individuals m.

Using the CPS enables us to estimate these quantities directly by leveraging reported incomes and program participation, along with tax simulation models (e.g., NBER TAXSIM) where needed to estimate liabilities. Migrant status is determined through self-reported country of birth and citizenship variables, allowing for disaggregation by migrant group (e.g., Mexican vs. non-Mexican migrants).

Second Approach: Macro-Level Allocation Using CBO Data and Population Shares

The second approach complements the micro-level analysis by incorporating aggregated fiscal data from the *Congressional Budget Office (CBO)*, which reports annual figures for federal revenue and expenditures across major programs.

To attribute portions of these totals to migrants and non-migrants, the analysis applies estimated population shares derived from CPS data. These shares serve as weights in allocating aggregate revenue and expenditure flows.

$$FB_N = FB_M \Rightarrow \sum_{t=1}^{T} \alpha_t Rev_{NM} - \sum_{t=1}^{T} \alpha_t SS_{NM} = \sum_{k=1}^{K} \alpha_k Rev_M - \sum_{k=1}^{K} \alpha_k SS_M \quad (20)$$

Where:

- α_t represents the share of the population composed of non-migrants in year t, calculated from CPS population weights.

- Rev_{NM} and SS_{NM} are the total revenue and expenditures reported by the CBO in year t and attributed to non-migrants using α_t.
- α_k represents the share of the population that are migrants in year k.
- Rev_M and SS_M are the corresponding fiscal aggregates assigned to migrants.

This method provides a broader view of fiscal contributions and costs, serving as a consistency check for the microdata approach and accommodating the possibility of underreporting or survey limitations in CPS.

Together, these methods allow for a comprehensive assessment of the *public costs and tax contributions* of Mexican migrants and U.S. citizens over the period 2007–2017. After estimating the fiscal balances, the analysis shifts focus to how individuals access public benefits and what factors influence this decision.

Specifically, the **probability of benefit utilization** will be estimated for three population segments:

1. U.S. citizens,
2. Non-Mexican migrants, and
3. Mexican migrants.

To explore temporal dynamics and potential shifts in access or behavior, a second set of regressions will incorporate time-fixed effects or year dummies. This enables a more nuanced understanding of how benefit usage patterns evolve over time and across population groups.

Data

For this chapter, two main sources are revised, and data are used from them:

1. Current Population Survey Annual Social and Economic Supplement (ASEC).
   In particular, for this research, the data used is based on the CPS ASEC (March)

data, these data sets are elaborated by the Center for Economic and Policy Research. It is available for the period and contains the original income data. In addition, contains supplementary information on the basic core CPS variables that allows us to approach more diverse research questions.[19]

2. Historical data from the Budget Congressional Office (CBO).
   Since 1975, the CBO has produced independent analyses of budgetary and economic issues to support the Congressional budget process. The CBO is strictly nonpartisan; conducts objective, impartial analysis; and it produces reports on relevant matters for Congressional Budget processes, but does not make policy recommendations, and each report and cost estimate summarizes the methodology underlying the analysis. In this sense, the CBO regularly publishes data to accompany some of its key reports. Part of that information is the historical data on revenues, outlays, and the deficit or surplus from 1962 through the most recent year completed.

Identification strategy

One of the reasons to use the CPER Annual Social Economic Complement of the Current Population Survey data is the possibility of identifying migrant individuals and their characteristics, including the Household, family and individual income dynamics. Also, the estimation for tax payments.

Therefore, by using the available data it is possible to identify individuals who report to have been born in Mexico and the U.S., with their citizenship status. Also, another key aspect is when they arrive to the U.S., this is important as we test the probability of accessing the social security and welfare system through time. The first parameter that is considered is being Mexican-born and non-Mexican-born, then the citizenship status. After the previous, if the individual is the head of the household and the composition of its household. Once this characterization is done, the access to benefits is identified by the unearned sources of income, at the individual level and as a household. It is important to mention that there are cases where there is more than one family per household, but this

[19]Center for Economic and Policy Research. 2019. March CPS Uniform Extracts, Version 1.1. Washington, DC.

does not mean that there is more than one household head, in these cases there are several family heads but one of them is the household head. In the same way, characterization is used to collect data on tax revenues.

For the identification of social security and welfare system benefits use, the variables that report income from social security, welfare programs, supplemental income security, Medicaid and Medicare support, unemployment compensation, workers support, veteran payments, survivors and disability benefits, and educational assistance. In addition, these variables were considered to identify if a person receives assistance or not, by using the reported amount received as an indicator of reception. In the case of health costs, the per capita average cost provided by the Center for MedicCare and MedicAid Services was imputed to the data, based on variables that identify the use of any of the health support. For the tax revenues, the marginal tax rate variable was used to estimate the amount of tax paid by one individual and the amount paid for MediCare deducted on the payroll (1.45% stated in the Federal Insurance Contribution Act, FICA). As robustness check, a second tax revenue variable was calculated using the estimated state and federal tax liabilities available, where there were no significant differences.

Descriptive statistics

In Table 18, the distribution of the migrant population is presented by citizenship and status and the use of assistance. In both cases for women and men, close to one third of the sample represents heads of household, and for the women on average the 5.7% have citizenship, while 7. 2% on average of men are citizens. By looking at the percentage of people receiving assistance we can see that in almost all years the percentage of people reporting some sort of assistance is higher than the the people reporting citizenship, this means that people without a legal citizen or residence status report to receive some sort of assistance, the same happens for women, and with a more significant difference. in both cases there is an incremental over time, proportionally to the overall number of migrants in the U.S..

Regarding the individuals born in the U.S., as shown in table 19, the percentage of people receiving assistance is more constant over time, for both women and men, with an

Table 18: Migrants distribution by characteristics

Year	Migrants										
	All	Men	HH head	Citizenship Status			Women	HH head	Citizenship status		
				all	citizen with assistance	Non citizen with assistance			all	citizen with assistance	Non citizen with assistance
2007	11,569,946	6,497,196	1,986,543	25.9%	4.8%	5.9%	5,072,750	1,576,723	20.9%	3.0%	7.4%
2008	11,620,846	6,447,047	2,098,786	27.0%	5.0%	5.5%	5,173,799	1,628,328	21.4%	4.8%	6.2%
2009	11,615,417	6,393,041	2,127,961	28.9%	6.9%	8.2%	5,222,376	1,626,499	22.1%	5.4%	7.9%
2010	11,580,017	6,388,115	1,981,482	31.7%	8.1%	9.7%	5,191,902	1,625,867	23.8%	6.0%	8.5%
2011	11,350,664	6,136,444	1,978,217	32.7%	8.1%	7.8%	5,214,220	1,682,979	25.7%	6.5%	8.8%
2012	11,623,364	6,225,011	2,138,317	33.1%	7.5%	7.9%	5,398,353	1,793,896	24.7%	6.8%	8.7%
2013	11,508,193	6,047,018	2,096,569	30.3%	7.4%	7.5%	5,461,175	1,889,275	27.7%	6.8%	7.3%
2014	11,180,555	5,819,828	2,033,002	32.7%	8.1%	5.6%	5,360,727	1,859,592	28.5%	5.9%	7.8%
2015	11,905,634	6,294,972	2,133,511	34.0%	7.6%	6.2%	5,610,662	1,920,666	25.1%	4.0%	6.9%
2016	11,713,403	6,142,724	2,119,862	36.0%	7.3%	7.6%	5,570,679	1,912,168	26.6%	6.3%	7.6%
2017	11,834,474	6,238,775	2,139,931	35.3%	8.3%	6.7%	5,595,699	1,977,267	30.0%	5.8%	7.9%

Source: ASEC, CPS.

average of 3.5% and 4.2% receiving assistance on average, respectively. Nevertheless, it is worth mention that in aggregate terms the balance of assistance is close to zero, as the percentage of women is higher than that of men. One thing to notice is how the households (HH) are conformed, the percentage of one person HH shows that the percentage of women with U.S. citizenship is higher for every yar than men and in the case for migrants the relationship between groups is exactly the opposite, in this sense the previous could be an indicator of the use of one or more assistance programs.

Table 19: Non-migrants distribution

Year	Total population in U.S.A.	US Citizens						
		All	Men	HH head	Assistance	Women	HH head	Assistance
2007	296,825,125	285,255,179	48.8%	14.0%	4.0%	51.2%	12.3%	3.3%
2008	299,106,314	287,485,468	48.8%	13.7%	3.9%	51.2%	12.1%	3.2%
2009	301,484,098	289,868,681	48.9%	13.5%	4.1%	51.1%	12.4%	3.4%
2010	304,280,759	292,700,742	48.9%	13.5%	4.6%	51.1%	12.2%	3.7%
2011	306,110,704	294,760,040	49.0%	13.3%	4.4%	51.0%	12.2%	3.8%
2012	308,827,977	297,204,613	48.8%	13.4%	4.5%	51.2%	12.4%	3.8%
2013	311,117,360	299,609,167	48.8%	13.5%	4.4%	51.2%	12.2%	3.7%
2014	313,396,206	302,215,651	48.9%	13.4%	4.2%	51.1%	12.1%	3.6%
2015	316,168,724	304,263,090	48.8%	13.2%	4.2%	51.2%	12.3%	3.5%
2016	318,869,187	307,155,784	48.9%	13.2%	4.2%	51.1%	12.2%	3.5%
2017	320,372,687	308,538,213	48.8%	13.3%	4.1%	51.2%	12.2%	3.5%
2018	323,156,705	311,208,584	48.9%	13.2%	4.1%	51.1%	12.2%	3.6%

Source: ASEC, CPS.

One of the hypotheses about the use of social security and welfare programs was that even though the head of the household did not have access to the benefits due to its citizenship status, she could have access through other family members or get some support directed to children; in this sense the number of children in the HH becomes a relevant characteristic to have in mind when analyzing the effect of migrants in the fiscal system. In this regard the average number of children by groups seems to be very similar for women migrants ad non-migrants. For men, there is a larger difference, but there is still no significant difference, as shown in table 20 and 21.

Table 20: Percentage of one person HH

			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
% of 1 person HH	Women	Non Mig	6.0%	6.2%	6.0%	5.8%	6.0%	6.0%	6.0%	6.1%	6.2%	6.2%	6.2%
		Mig	1.3%	1.4%	1.3%	1.0%	1.3%	1.6%	1.8%	1.8%	1.7%	1.7%	1.9%
	Men	Non Mig	4.6%	4.6%	4.6%	4.6%	4.7%	4.8%	4.8%	4.7%	4.9%	5.0%	4.9%
		Mig	2.1%	2.3%	2.1%	1.6%	2.0%	2.3%	2.4%	2.6%	2.9%	2.6%	2.8%

Source: ASEC, CPS.

Table 21: Average number of children in a HH

			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Average # of children in the HH	Women	Non Mig	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.0	1.0
		Mig	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.0	1.0	1.0	1.0
	Men	Non Mig	1.8	1.8	1.8	1.8	1.8	1.7	1.6	1.6	1.6	1.5	1.4
		Mig	1.4	1.5	1.4	1.5	1.6	1.5	1.4	1.4	1.4	1.3	1.3

Source: ASEC, CPS.

In Table 22 the average time in the U.S. since arrival shows that for migrants, without regard of gender, the average time is more than 10 for the group that reports to receive some sort of assistance, and for the groups that reported the opposite, the average time is almost the double every year. The previous fits the idea that people use the system in the first stages of reallocation, and once the individuals are settled, they stop receiving assistance. In this sense, the result helps to understand in tandem with the findings on previous chapters, reinforce the idea of positive effects and spillovers of migration in the host countries.

Table 22: Average time in the U.S.

			2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Average time in US	Women	beneficiary	14.3	14.7	15.3	15.5	16.5	17.3	17.9	17.9	18.8	19.5	20.2
		non beneficiary	26.3	27.1	26.4	26.6	25.9	27.4	28.3	29.1	27.8	29.1	31.2
	Men	beneficiary	13.3	14.2	14.7	15.6	16.1	17.2	17.6	18.6	18.6	19.9	20.0
		non beneficiary	28.8	27.9	26.6	25.7	26.4	27.0	29.4	30.5	29.5	29.7	31.8

Source: ASEC, CPS.

Results

In this section the results of all exercises are going to be presented in the following order: first, the results of the fiscal balance of the social security and welfare system based on the data from the ASEC; secondly, the fiscal balance based on the BCO data and group shares extracted from the ASEC data; third, the results of the probit regressions for U.S. citizens, non-Mexican migrants and Mexican migrants; finally, the results of the probit regressions for Mexican migrants having the time effects considered.

Fiscal balance assessment: first approach.

In this approach the fiscal balance is calculated based on data reported through ASEC surveys, the results are presented in Table 23 and 24, and it can be seen the average difference of total tax revenues minus the total benefits received by a group of U.S. citizens, Mexican individuals born in Mexico and with U.S. citizenship, and Mexican migrants without legal status. The previous in order to better understand the dimensions of use and access to benefits of each group.

For the women group, there is a consistent deficit, where the U.S. citizen groups is the one that on average is heavier in terms of costs (tax revenues - assistance costs); following this logic the second group in magnitude is the Mexican migrants and finally the Mexican born U.S. citizens. In the case of men there is also a clear deficit, but a more significant difference is present in the Mexican group, following in second the U.S. citizen group, and, also in this case, the Mexican born U.S. citizens are the ones that cost the least. This distinction allows us to understand at a micro level the comparison of representative individuals. It is important to remember that these differences were calculated by identifying the heads of the household, but also taking into account the composition of the household.

Table 23: Fiscal balance: first approach

	Fiscal balance (CPS, 2007 - 2018) Average individual difference					
	Women			Men		
	US citizen	Mex migrant (US citizen)	Mex migrants (non US Citizen)	US citizen	Mex migrant (US citizen)	Mex migrants (non US Citizen)
2007	-2042.57	-1276.86	-1783.44	-352.19	255.34	-428.58
2008	-2079.16	-1473.82	-2181.34	-400.69	-19.40	-752.08
2009	-2384.93	-1459.13	-2708.34	-934.76	-265.71	-1149.24
2010	-3102.52	-2061.13	-3271.95	-1786.44	-937.11	-2001.14
2011	-2317.32	-1866.19	-2431.47	-487.52	-393.60	-1322.28
2012	-2332.41	-1579.08	-3084.22	-422.16	-603.87	-1069.43
2013	-2495.91	-1877.25	-3494.25	-477.90	-649.37	-1421.69
2014	-2659.41	-2175.43	-3904.28	-533.65	-694.87	-1773.94
2015	-2995.06	-2606.96	-3363.05	-1130.89	-449.97	-996.19
2016	-2676.56	-2635.53	-3459.55	-543.85	-897.37	-1612.80
2017	-2602.74	-2172.11	-3270.90	-48.85	-202.75	-1846.95

Source: ASEC, CPS.

Another way to see the differences presented is to compute a ratio of total taxes revenue over total benefits received following the same structure for the comparison. In this sense having a value below 1 means that there is a deficit, and over 1 means superavit. In table 25, these results are shown, where there are a few cases with a ratio over 1, that is, with superavit. The previous also allow us to understand the magnitude between the differences. This is relevant in terms of how much tax collection helps to fund the social security and welfare system. In the case of women U.S. citizens, the average ratio is 0.85, for Mexican born U.S. citizens 0.13, and for Mexican migrants 0.48, the previous show how each group is being funded, the closer to the unit the highest level of ”self-fundedness”, but let us remember that people without citizenship do not have general and straightforward access to the system benefits and they cannot have a job in the formal market; therefore, there is no direct way for them to pay taxes. Regarding the men's groups, on average the U.S. citizen groups show a superavit, but for both Mexican born groups, with and without U.S. citizenship, there is a clear deficit with a ratio of 0.30 and 0.35, respectively.

Table 24: Fiscal balance: first approach

	Fiscal balance (CPS, 2007 - 2018) Average ratio (tax collection/benefit payments)					
	Women			Men		
	US citizen	Mex migrant (US citizen)	Mex migrants (non US Citizen)	US citizen	Mex migrant (US citizen)	Mex migrants (non US Citizen)
2007	0.70	0.15	0.08	2.84	0.16	0.25
2008	0.66	0.05	0.14	0.90	0.27	0.13
2009	0.59	0.15	0.15	2.89	0.51	0.27
2010	1.37	0.14	0.27	1.64	0.20	0.54
2011	0.87	0.09	0.20	0.86	0.19	0.59
2012	0.53	0.10	0.23	4.75	0.45	0.44
2013	0.44	0.10	0.17	2.83	0.37	0.37
2014	0.35	0.09	0.11	0.92	0.29	0.31
2015	2.26	0.09	3.45	1.24	0.27	0.44
2016	0.86	0.20	0.15	1.83	0.26	0.31
2017	0.74	0.23	0.31	5.12	0.33	0.23

Source: ASEC, CPS.

Overall, the results of this approach showed a different behavior between the groups but a constant dynamic within the groups. The reason for a second approach is to take in consideration the size of the groups and relate them with the budget data from the U.S., with the aim of having a clearer picture of costs and contributions for a clearer analysis of the fiscal implications of migration.

Fiscal balance assessment: second approach.

As was described in the identification strategy, the way that this is computing the group shares generated with the ASEC data is added to historical budget data published by the Congressional Budget Office. This approach, as mentioned, allows to have a broader and clearer picture of the fiscal net balance for each group. First, in table 25 the shares for migrants and non-migrants for each of the mandatory outlays categories, using the variables that identify the access to each of the concepts presented: social security, MedicAid, MediCare, Supplementary Security Income Income complements, Veterans programs, and welfare complementary programs.

In Table 26 the taxes revenues from individual income tax and payroll taxes is presented; this in tandem with the shares by group, gives the results of Table 29, where the fiscal balance for each group is shown for each year. In the case of U.S. citizens, there is a change

Table 25: Fiscal Balance: second approach

Total benefits outlays for Non-migrants and Migrants (Bllns of dlls)

	Social Security		MedicAid		MedicCare		Supplementary Security Income		Income Complements		Veteran´s Program		Welfare Complementary	
	Non mig	Mig	Non mig	Mig	Non mig	Mig	Non mig	Mig	Non mig	Mig	Non mig	Mig	Non mig	Mig
2007	572.72	8.73	183.87	6.75	429.89	6.22	196.36	6.75	117.64	4.77	38.41	0.02	52.58	3.20
2008	602.87	9.24	194.42	7.01	449.25	6.74	254.07	6.58	123.87	5.01	44.36	0.17	72.77	3.98
2009	665.85	11.87	242.08	8.84	492.15	7.78	341.26	8.96	132.35	5.30	49.33	0.27	303.52	18.25
2010	688.04	12.71	263.11	9.66	512.53	7.95	426.70	10.59	133.12	5.27	57.91	0.35	-16.56	-1.20
2011	712.12	12.80	266.35	8.61	550.49	9.16	394.06	9.98	138.81	5.35	70.62	0.39	53.59	2.53
2012	754.96	12.76	242.29	8.24	542.38	8.77	345.96	7.63	138.12	5.40	67.90	0.09	116.59	7.63
2013	793.40	14.44	256.53	8.86	575.21	10.01	330.82	8.68	146.86	5.64	80.07	0.31	100.40	5.06
2014	829.29	15.58	290.28	11.19	589.76	10.05	303.00	7.89	151.89	5.62	86.29	0.47	70.05	4.43
2015	865.98	15.91	335.52	14.24	623.05	11.06	294.03	6.98	155.38	6.08	91.99	0.45	125.30	8.94
2016	892.28	18.00	351.98	16.30	678.72	13.77	295.25	8.53	157.77	6.02	105.73	0.79	110.89	8.88
2017	921.33	17.88	358.19	16.49	687.87	14.41	286.25	7.55	156.55	6.00	104.25	0.75	186.22	8.49

Source: CBO.

in direction in 2009, from deficit to superavit. For the migrants group the results show a clear deficit over the whole period, the previous is also expected as the tax collection through the concept considered; but the result that appears significant and important is the ratio results, where the average ratio of funding is 0.54, in this sense the relationship between the tax revenues and the benefits costs is close to the unit.

Table 26: Fiscal Balance: second approach

Total tax revenues

	Individual Income	Payroll Taxes	Total Revenue
2007	1163.47	869.61	2033.08
2008	1145.75	900.16	2045.90
2009	915.31	890.92	1806.23
2010	898.55	864.81	1763.36
2011	1091.47	818.79	1910.27
2012	1132.21	845.31	1977.52
2013	1316.41	947.82	2264.23
2014	1394.57	1023.46	2418.03
2015	1540.80	1065.26	2606.06
2016	1546.08	1115.07	2661.14
2017	1587.12	1161.90	2749.02

Source: CBO.

The results of both approaches showed similar results for U.S. citizens, where there is a superavit in the first approach for the men's group and for the overall group in the second

Table 27: Fiscal Balance: second approach

Non-migrants and Migrants

	Total Spending		Total Tax Revenue (from payroll and income taxes)		Public Deficit (S - R)		Public Deficit Ratio (S/R)	
	Non mig	Mig	Non mig	Mig	Non mig	Mig	Non mig	Mig
2007	1591.48	36.44	1934.98	98.10	-343.50	-61.66	0.82	0.37
2008	1741.60	38.73	1949.14	96.76	-207.54	-58.03	0.89	0.40
2009	2226.54	61.28	1720.30	85.93	506.24	-24.65	1.29	0.71
2010	2064.86	45.33	1678.72	84.64	386.14	-39.31	1.23	0.54
2011	2186.03	48.81	1820.13	90.14	365.90	-41.32	1.20	0.54
2012	2208.19	50.53	1881.24	96.28	326.95	-45.75	1.17	0.52
2013	2283.30	53.01	2180.47	83.75	102.83	-30.75	1.05	0.63
2014	2320.56	55.23	2308.21	109.81	12.35	-54.58	1.01	0.50
2015	2491.25	63.66	2478.82	127.24	12.43	-63.57	1.01	0.50
2016	2592.62	72.29	2534.38	126.76	58.24	-54.46	1.02	0.57
2017	2700.66	71.57	2618.92	130.09	81.73	-58.52	1.03	0.55

Source: CBO.

approach; maintaining a deficit for the groups of migrants in both exercises. The reason to not make the distinction between Mexican-born U.S. citizens and Mexican Migrants in the second approach is that there is no difference in the results, and not doing it creates a better picture of migration as a overall phenomenon in the social security and welfare fiscal dynamics.

Regressions

There are several factors that intervene in the capacity of an individual to generate sufficient income to maintain their HH, in this sense those characteristics determine the likelihood of requiring some sort of government assistance. Therefore, to have a better idea of the effect of migration in the fiscal system through the access and use of the security and welfare assistance system, the possibility that an HH receives monetary assistance helps to understand and forecast the functionality and evolution of the programs and what sort of demographic changes could impact significantly on the budget and public policy provisions. For the previous, the following probit regression is estimated:

$$Asistance_i = \alpha + \beta_i X_i + Ui$$

Where the dependent variable is a dummy var that identifies the people who are beneficiaries of one or more programs of the social security and welfare system, α is the intercept, β_i is the coefficient for the vector X_i of demographic characteristics and u_i is the error term. The social security and welfare system considers the following categories of assistance:

0: Without assistance

1: public assistance and welfare

2: social security or railroad

3: supplementary security

4: unemployment compensation

5: worker's compensation

6: veteran payments

7: survivor's benefits

8: disability

9: educational assistance

10: MediCare/MedicAid

In Table 28, the results show that for U.S. citizens, there is a negative effect on the probability of accessing an assistance program with the presence of any level of education (high school, some college and advanced)[20], having children in the HH, and being married. On the contrary, there is a positive effect on the probability when the individual is a woman; also, the probability increases with age. For the non-migrant groups having a legal status

[20] For this categorical variable the reference group is having an educational level lower than high school)

Table 28: Results, Social security and welfare assistance probability for US born citizens (1), foreing born migrants (2) and Mexican born migrants (3)

	(1) assist	(2) assist	(3) assist
assist			
Citizenship		0.189**	0.237**
		(0.000199)	(0.000351)
HS	-0.255**	-0.0930**	-0.108**
	(0.000116)	(0.000289)	(0.000380)
Some college	-0.177**	0.132**	0.162**
	(0.000117)	(0.000309)	(0.000505)
College	-0.563**	-0.227**	-0.176**
	(0.000129)	(0.000312)	(0.000808)
Advanced	-0.661**	-0.280**	-0.240**
	(0.000147)	(0.000352)	(0.00136)
Age	0.0393**	0.0397**	0.0350**
	(0.00000189)	(0.00000604)	(0.0000113)
H head	0.0195**	-0.00212**	0.127**
	(0.0000684)	(0.000200)	(0.000327)
Female	0.0152**	0.00462**	0.0808**
	(0.0000611)	(0.000187)	(0.000314)
Children	-0.362**	-0.00903**	-0.256**
	(0.000208)	(0.000994)	(0.00210)
Married	-0.514**	-0.500**	-0.304**
	(0.0000686)	(0.000198)	(0.000330)
Constant	-1.830**	-2.491**	-2.633**
	(0.000139)	(0.000408)	(0.000622)
Observations	2,305,971,948	295,213,068	121,814,264
Pseudo R^2	0.217	0.226	0.164

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

has a positive effect, in the same direction as for the U.S. citizens, being a woman has a positive effect, the same for age. There is a mixed outcome for educational attainment in both groups of migrants where for individuals with college there is also a positive effect, but for the rest of the categories the effect is negative.

Table 29: Results, Social security and welfare assistance probability for US born citizens (1), foreign born migrants (2) and Mexican born migrants (3)

	(1) assist	(2) assist	(3) assist
Citizenship		0.0420**	0.0463**
		(0.0000432)	(0.0000670)
HS	-0.0688**	-0.0211**	-0.0200**
	(0.0000)	(0.0000)	(0.0000)
Some college	-0.0466**	0.0341**	0.0296**
	(0.0000)	(0.0000)	(0.0000)
College	-0.152**	-0.0494**	-0.0331**
	(0.0000)	(0.0000)	(0.0001)
Advanced	-0.176**	-0.0603**	-0.0412**
	(0.0000)	(0.0000)	(0.0001)
Age	0.0107**	0.00907**	0.00639**
	(0.00000)	(0.0000)	(0.00000)
H head	0.00465**	-0.000953**	0.0216**
	(0.0000)	(0.0000)	(0.0000)
Female	0.00432**	0.000594**	0.0155**
	(0.0000)	(0.0000)	(0.0000)
Children	-0.0949**	0.00202**	-0.0415**
	(0.0000)	(0.0002)	(0.0002)
Married	-0.138**	-0.119**	-0.0581**
	(0.0000)	(0.0000)	(0.0000)
Observations	2524628848	327002868	133540300

Standard errors in parentheses
+ p¡.1, * p¡0.05, ** p¡0.01

In table 29, the marginal effects from the probit regression are presented where it is possible to see the effect that each independent variable have over the probability of using one of the components of assistance within the social security and welfare system of the

U.S.. There are mixed directions between U.S citizens and foreign-born individuals. For example, the effect of having some college is negative for U.S. citizens but positive for the foreign-born categories, with -0.177, 0.132 and 0.162 respectively. Having some college as a female will reduce the probability of using the social security and welfare system in 0.04195, 0.0488 and 0.0176 for U.S. citizens, foreign-born individuals, and Mexican born individuals. In this case, the lower effect is on the Mexican woman as the effect of being a woman is highest between the groups. Having the citizenship is one of the main factors that increase the probability of accessing the system; in the case of U.S citizens this variable was dropped due to collinearity. But what can be inferred is that as all citizens already have access to the system, this is not a determinant factor while in the case of the other two groups it is.

In order to have a clearer picture of the determinants for each category of assistance a multinomial logit regression is estimated.

$$AsistanceCategory_i = \alpha_{ij} + \beta_{ij} X_{ij} + U_{ij}$$

Here, the dependent variable is a categorical variable that takes 10 values representing the sort of assistance, considering the characterization done for the assistance variable. The α is the intercept for each individual i and category j, β_{ij} is the coefficient for the vector X_{ij} of demographic characteristics (citizenship, level of education attained - lower than high school, high school, some college, college and advanced degree-, age, household head, gender, children's in the household, and marital status) and u_{ij} is the error term.

In Table 30 the summary of the results is presented, detailed results for each category are presented in the annex, and it shows that the effects remain significant as in the probit regression for all the categories; also, in terms of the direction of the coefficients.

To incorporate the effect of time, the same variables are considered in the regression, but in this case there is a variable that collects the time that a person has in the U.S. since the arrival; these variables follow an increment of two years as that is the way the data is collected by the survey. This variable is introduced through an interaction between being

Table 30: Results, Social security and welfare assistance probability by category: Summary

	(1) assist_cat	(2) assist_cat	(3) assist_cat	(4) assist_cat
MediCare_MedicAid Baseline				
Abreviated Results				
Citizenship	Sig.	No Sig.	Sig.	Sig.
HS	Sig.	Sig.	Sig.	Sig.
Some college	Sig.	Sig.	Sig.	Sig.
College	Sig.	Sig.	Sig.	Sig.
Advanced	Sig.	Sig.	Sig.	Sig.
Age	Sig.	Sig.	Sig.	Sig.
H head	Sig.	Sig.	Sig.	Sig.
Female	Sig.	Sig.	Sig.	Sig.
Children	Sig.	Sig.	Sig.	Sig.
Married	Sig.	Sig.	Sig.	Sig.
Constant	Sig.	Sig.	Sig.	Sig.
Observations	2,985,172,016	2,524,628,848	327,002,868	133,540,300
ML R^2	0.457	0.468	0.402	0.256
McFadden Pseudo R^2	0.299	0.299	0.308	0.241
Cragg & Uhler's R2 (Nagelkerke)	0.525	0.532	0.495	0.363

Standard errors in parentheses
+ p¡.1, * p¡0.05, ** p¡0.01

a migrant and the time since the arrival. The regression is grouped by year.

$$Asistance_i = \alpha_{ij} + \beta_{ij}X_{ij} + \gamma_i(TimeInUS_tXMigrant_i) + Ui + \tau_t$$

Here $TimeInUS_tXMigrant_i$ is the interaction term, γ_i is the coefficient of the interaction and tau_t is the time error term. The results presented in Tables 31 and 32 are for the entire period, that is, 2007 - 2017. where for all the years where having citizenship has a positive impact, and the same for age. All levels of educational attainment show a negative effect on the likelihood of being a beneficiary, the same for having children and being married. Being a woman also has a positive effect. Being a head of the HH has a positive effect for the period 2007 - 2015, but for the last two years, it shows a negative effect. One interesting result are the coefficients of the interactions, as it shows a significant negative effect on the probability of receiving support from an assistance program.

Also, being a woman means the same for all the years with a positive effect on the probability, the same happens for being a migrant or U.S. citizen, the likelihood is positive. However, it is also important to mention that the hypothesis of the effect of time on the probability of having government support through the social security and welfare system is negative and constant in time; therefore, migrants tend to desist from the use of the assistance system with time.

Table 31: Results, Social security and welfare assistance probability (pt. I)

	(1) 2007	(2) 2008	(3) 2009	(4) 2010	(5) 2011	(6) 2012
Citizenship	0.406**	0.397**	0.369**	0.396**	0.402**	0.391**
	(0.000596)	(0.000575)	(0.000563)	(0.000517)	(0.000518)	(0.000499)
Educational attainment						
LTHS	-0.0747**	-0.0993**	-0.0888**	-0.111**	-0.0999**	-0.0801**
	(0.000550)	(0.000562)	(0.000547)	(0.000548)	(0.000550)	(0.000552)
HS	-0.287**	-0.346**	-0.309**	-0.278**	-0.264**	-0.245**
	(0.000489)	(0.000502)	(0.000489)	(0.000487)	(0.000488)	(0.000491)
Some college	-0.245**	-0.261**	-0.233**	-0.222**	-0.177**	-0.145**
	(0.000501)	(0.000512)	(0.000499)	(0.000497)	(0.000498)	(0.000500)
College	-0.623**	-0.624**	-0.623**	-0.573**	-0.592**	-0.546**
	(0.000530)	(0.000539)	(0.000526)	(0.000519)	(0.000521)	(0.000522)
Advanced	-0.693**	-0.743**	-0.722**	-0.722**	-0.696**	-0.657**
	(0.000585)	(0.000591)	(0.000574)	(0.000568)	(0.000564)	(0.000564)
Age	0.0414**	0.0413**	0.0389**	0.0366**	0.0359**	0.0369**
	(0.00000637)	(0.00000632)	(0.00000610)	(0.00000590)	(0.00000582)	(0.00000580)
H head	0.0524**	0.0298**	0.0347**	0.0452**	0.0327**	0.0302**
	(0.000221)	(0.000221)	(0.000214)	(0.000208)	(0.000207)	(0.000205)
Women	0.0363**	0.0336**	-0.00713**	-0.0384**	-0.0196**	0.0105**
	(0.000201)	(0.000199)	(0.000193)	(0.000188)	(0.000186)	(0.000185)
Children	-0.238**	-0.239**	-0.311**	-0.445**	-0.469**	-0.365**
	(0.000675)	(0.000671)	(0.000654)	(0.000664)	(0.000668)	(0.000652)
Married	-0.544**	-0.537**	-0.534**	-0.512**	-0.501**	-0.488**
	(0.000222)	(0.000221)	(0.000215)	(0.000208)	(0.000207)	(0.000206)
Interaction						
Time in U.S. X Migrant						
2 yrs × Mig	-0.857**	-1.163**	-0.794**	-0.484**	-0.508**	-0.951**
	(0.00295)	(0.00491)	(0.00302)	(0.00393)	(0.00338)	(0.00577)
4 yrs × Mig	-0.746**	-0.421**	-0.660**	-0.509**	-0.444**	-0.393**
	(0.00343)	(0.00316)	(0.00319)	(0.00393)	(0.00333)	(0.00379)
6 yrs × Mig	-0.667**	-0.945**	-0.472**	-0.270**	-0.414**	-0.313**
	(0.00271)	(0.00446)	(0.00277)	(0.00287)	(0.00259)	(0.00308)
8 yrs × Mig	-0.724**	-0.574**	-0.585**	-0.364**	-0.488**	-0.415**
	(0.00310)	(0.00294)	(0.00246)	(0.00293)	(0.00275)	(0.00289)
10 yrs × Mig	-0.484**	-0.345**	-0.368**	-0.0729**	-0.275**	-0.327**
	(0.00139)	(0.00171)	(0.00135)	(0.00156)	(0.00126)	(0.00151)
Constant	-2.236**	-2.314**	-2.048**	-2.175**	-1.996**	-2.082**
	(0.00128)	(0.00165)	(0.00129)	(0.00153)	(0.00122)	(0.00147)
Observations	236020411	238148000	240144848	242168581	243955447	247697054

Standard errors in parentheses
+ p¡.1, * p¡0.05, ** p¡0.01

Table 32: Results, Social security and welfare assistance probability (pt. II)

	(1) 2013	(2) 2014	(3) 2015	(4) 2016	(5) 2017
Citizenship	0.412**	0.442**	0.396**	0.452**	0.449**
	(0.000518)	(0.000513)	(0.000509)	(0.000508)	(0.000513)
Educational Attainment					
LTHS	0.00662**	-0.00999**	0.00166**	-0.0243**	-0.0220**
	(0.000568)	(0.000572)	(0.000578)	(0.000582)	(0.000605)
HS	-0.170**	-0.163**	-0.163**	-0.166**	-0.181**
	(0.000502)	(0.000503)	(0.000505)	(0.000512)	(0.000531)
Some college	-0.0697**	-0.0490**	-0.0598**	-0.0673**	-0.0656**
	(0.000510)	(0.000511)	(0.000513)	(0.000519)	(0.000539)
College	-0.487**	-0.450**	-0.448**	-0.448**	-0.423**
	(0.000532)	(0.000531)	(0.000533)	(0.000538)	(0.000555)
Advanced	-0.554**	-0.526**	-0.519**	-0.533**	-0.494**
	(0.000569)	(0.000569)	(0.000569)	(0.000571)	(0.000586)
Age	0.0385**	0.0388**	0.0398**	0.0402**	0.0408**
	(0.00000584)	(0.00000582)	(0.00000581)	(0.00000576)	(0.00000575)
H head	0.0156**	0.00260**	0.0102**	-0.00166**	-0.0115**
	(0.000207)	(0.000208)	(0.000209)	(0.000208)	(0.000208)
Women	0.0250**	0.0174**	0.0298**	0.0258**	0.0350**
	(0.000186)	(0.000186)	(0.000187)	(0.000186)	(0.000187)
Children	-0.338**	-0.251**	-0.201**	-0.127**	-0.224**
	(0.000666)	(0.000671)	(0.000671)	(0.000655)	(0.000698)
Married	-0.511**	-0.499**	-0.511**	-0.498**	-0.508**
	(0.000207)	(0.000208)	(0.000209)	(0.000208)	(0.000208)
Interaction					
Time in U.S. X Migrant					
2 yrs × Mig	-0.574**	-0.380**	-0.459**	-0.207**	-0.472**
	(0.00379)	(0.00435)	(0.00283)	(0.00352)	(0.00353)
4 yrs × Mig	-0.467**	-0.578**	-0.482**	-0.333**	-0.895**
	(0.00365)	(0.00478)	(0.00398)	(0.00409)	(0.00461)
6 yrs× Mig	-0.391**	-0.392**	-0.184**	-0.239**	-0.367**
	(0.00294)	(0.00413)	(0.00319)	(0.00350)	(0.00355)
8 yrs× Mig	-0.316**	-0.370**	-0.168**	-0.119**	-0.311**
	(0.00262)	(0.00316)	(0.00250)	(0.00291)	(0.00343)
10 yrs× Mig	-0.458**	-0.337**	-0.575**	-0.556**	-0.443**
	(0.00124)	(0.00143)	(0.00115)	(0.00129)	(0.00114)
Constant	-2.127**	-2.287**	-2.191**	-2.258**	-2.352**
	(0.00120)	(0.00140)	(0.00110)	(0.00126)	(0.00112)
Observations	250023912	252344947	255188341	257904010	259403729
Pseudo R^2	0.217	0.217	0.226	0.230	0.238

Standard errors in parentheses
+ p¡.1, * p¡0.05, ** p¡0.01

Conclusions

Migration dynamics is constantly changing due to global, regional, and local contextual changes, making it essential to continuously assess its impact on both host and home countries. This continuous evaluation is critical, as it provides vital insights for policymakers and other stakeholders involved in migration-related decisions. The analysis in this chapter of Mexican migrants' effects on the U.S. social security and welfare systems reveals a persistent fiscal deficit among migrant groups, irrespective of their citizenship status. This observation highlights the structural disparities between legal and illegal migrants, emphasizing the potential for increasing tax revenues if undocumented migrants were granted legal residency. Even though these migrants might gain access to social security and welfare programs, the overall fiscal impact could become more balanced, as pointed out by (Sand & Razin, 2006).

As discussed in the introduction, ”migrants tend to cost more than what they bring”, but this deficit can be mitigated by policies that enhance their formal labor market integration. This underscores the urgency for changes in migration policy that establish mechanisms to balance public expenditures and revenues within the social security and welfare systems. As Borjas, 1995a asserts, the fiscal impacts of immigration are deeply intertwined with the way public resources are allocated and utilized. Addressing this issue is critical, as migration, while fluctuating in flow, is an enduring phenomenon. The findings of this chapter call for timely action to develop more efficient frameworks that ensure fiscal sustainability, creating a system that can equitably balance the needs of migrants with the long-term stability of U.S. fiscal policy.

Moreover, the analysis shows that Mexican migrants contribute significantly to tax revenues through payroll and income taxes, but their limited access to benefits due to legal status shapes the overall fiscal balance. As noted in Borjas (2019), legal status significantly influences the net fiscal contribution of migrants, as undocumented migrants often contribute without fully benefiting from the system. Policy changes, such as granting legal residency to undocumented migrants, could result in higher tax revenues, even though it might lead to increased access to social security and welfare benefits. It is also important to emphasize the importance of adapting policies to account for these dynamics, reinforcing the need for flexible frameworks that respond to evolving migration trends.

The research also highlights that over time, Mexican migrants who remain in the U.S. gradually reduce their reliance on welfare systems, suggesting that better integration results in improved economic performance. This aligns with G. Hanson et al. (2023), who discuss how evolving migration patterns and legal frameworks can shift fiscal impacts as migrants become more economically assimilated. Finally, this chapter reinforces the notion from the introduction that migration policy must adapt to the evolving dynamics of migrant populations. By recognizing the changing composition and fiscal contributions of Mexican migrants, U.S. policies can foster a more sustainable and equitable social security and welfare system.

Annex

Chapter I

First Stochastic Dominance

Def.

Following (**Borjas2018**) let $F_M^j(z)$ and $F_N^j(z)$ represent the cumulative probability distributions of skills or earnings for migrants and non-migrants in the source country, respectively, given the j group of individuals, where z denotes a particular measure of skills (e.g., observable or unobservable characteristics or income). By definition, the probability distribution of migrants $F_M^j(z)$ is first-order stochastically dominated by that of stayers $F_N^j(z)$ if:

$$F_M^j(z) \geq F_N^j(z) \ \ \forall \quad z \sim N(0, \sigma_z^2) \quad \& \quad j = 1, ..., J. \tag{21}$$

The last imply that if the probability of distribution of stayers stochastically dominates that of migrants, with negative selection, then $E^j(z|I > 0) < E^j(z|I < 0)$.

Second Stochastic Dominance

Def.

For any lotteries F and G, F second-order stochastically dominates G if and only if the decision maker weakly prefers F to G under every weakly increasing concave utility function u.

For any lotteries F and G, G is a mean-preserving spread of F if and only if $y = x+$ for some xF, yG and such that $E(\epsilon|x) = 0$ for all x. Imagine that for every realization x, we add a noise and give the decision maker $y = x+$. Since $E(\epsilon|x) = 0$, this only makes consumption more risky without improving its expectation. In other words, we are spreading the probabilities without changing the mean. If the decision maker is risk averse, she would not like to have this scheme. She prefers to consume x.

Before stating this formally, it is instructive to compare this scheme with the one in the first-order stochastic dominance. In that case, we were giving him an extra amount of consumption at each realization x. While this could increase the variance of consumption, the decision maker knew that she was getting more. She liked that scheme. Here, we are increasing the variance without increasing the expectation. He can gain or lose by the change. Being risk-averse implies that she does not like the change.

Given that FOSD $\Rightarrow$ SOSD, under certain conditions, we could expect that the characterization of the model holds. But in this case, it is worth the effort to revise how the conditions imposed by the SOSD could affect the FOSD, also having in mind the ex-ante characterization done through the risk aversion measure. In this sense, by comparing the distributions given the possible earnings of migration or staying is less risky or more suitable for the group profiles.

Given $F^j_M(z)$ and $F^j_N(z)$, $F^j_M(z)$ second-order stochastically dominates $F^j_N(z)$ if the decision maker weakly prefers $F^j_M(z)$ to $F^j_N(z)$ under an increasingly concave function that represents her preferences. In other words $E^j_M(z) \geq E^j_N(z)$.

Therefore, we can summarize the sufficient conditions for SOSD:

- $F^j_M(z)$ FOSD $F^j_N(z)$
- if $F^j_N(z)$ is a mean-spred of $F^j_M(z)$, then $F^j_M(z)$ SOSD $F^j_N(z)$

Necessary conditions for SOSD:

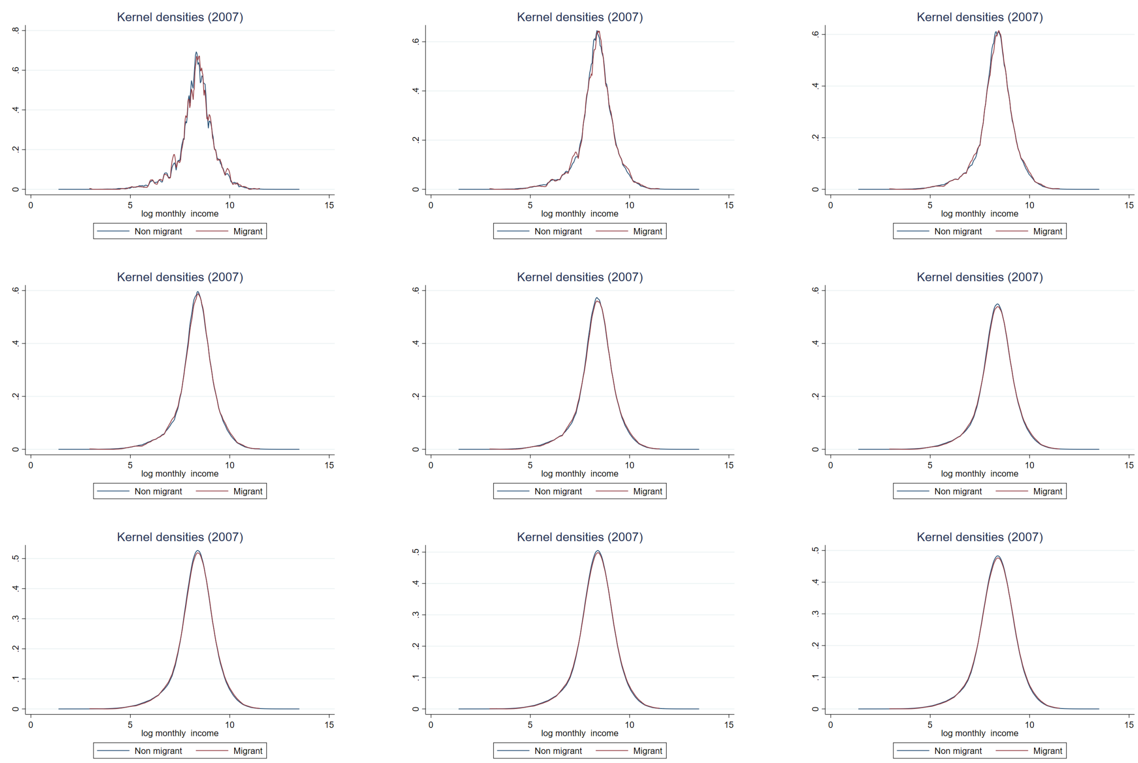
- $E^j_M(z) \geq E^j_N(z)$
- $(min\{z\}|F^j_M(z)) \geq (min\{z\}|F^j_N(z))$

With these conditions, it is possible to confirm which distribution dominates, then we can characterize the selection bias accordingly.

Kernel estimations - bandwidth exercise example

The purpose of this exercise is to demonstrate the evolution of the graphs as the bandwidth increases in increments of 0.1, within the range of 0.15 to 1. This aims to show that the relationship between the density estimations of the groups remains consistent throughout the incremental changes.

Figure 29: Kernel density estimations - bandwidth increases of .1 exercise



Chapter III

Multinomial Logit Regression results by category

Table 33: Results, Social security and welfare assistance probability by category: without assistance.

	(1)	(2)	(3)	(4)
	assist_cat	assist_cat	assist_cat	assist_cat
Not aplicable (without assistance)				
Citizenship	1.461**	0	0.632**	0.576**
	(0.000713)	(.)	(0.00100)	(0.00171)
HS	-0.457**	-0.635**	-0.194**	-0.351**
	(0.000354)	(0.000385)	(0.00120)	(0.00215)
Some college	-0.482**	-0.678**	-0.0800**	-0.0135**
	(0.000365)	(0.000394)	(0.00132)	(0.00270)
College	-1.235**	-1.435**	-0.656**	-0.446**
	(0.000441)	(0.000474)	(0.00143)	(0.00443)
Advanced	-1.441**	-1.633**	-0.963**	-0.547**
	(0.000520)	(0.000554)	(0.00178)	(0.00704)
Age	0.105**	0.106**	0.108**	0.0984**
	(0.0000112)	(0.0000118)	(0.0000449)	(0.0000733)
hhead	0.311**	0.328**	0.224**	0.309**
	(0.000244)	(0.000257)	(0.000941)	(0.00170)
Female	-0.0842**	-0.0775**	-0.0341**	0.0669**
	(0.000221)	(0.000231)	(0.000874)	(0.00164)
Children	-0.560**	-0.724**	0.412**	-21.20**
	(0.00182)	(0.00185)	(0.0106)	(0.00344)
Married	-1.480**	-1.488**	-1.297**	-0.808**
	(0.000238)	(0.000252)	(0.000885)	(0.00165)
Constant	-8.570**	-6.960**	-8.922**	-8.839**
	(0.000964)	(0.000765)	(0.00315)	(0.00447)

Standard errors in parentheses
+ p¡.1, * p¡0.05, ** p¡0.01

Table 34: Results, Social security and welfare assistance probability by category: Income from public assistance and welfare.

	(1) assist_cat	(2) assist_cat	(3) assist_cat	(4) assist_cat
Income from public assistance				
Citizenship	-0.0968**	0	-0.422**	-0.336**
	(0.000796)	(.)	(0.00192)	(0.00266)
HS	-0.622**	-0.647**	-0.635**	-0.584**
	(0.000690)	(0.000802)	(0.00199)	(0.00215)
Some college	-1.289**	-1.322**	-1.143**	-1.375**
	(0.000796)	(0.000885)	(0.00250)	(0.00436)
College	-2.399**	-2.549**	-1.838**	-1.573**
	(0.00141)	(0.00163)	(0.00311)	(0.00778)
Advanced	-2.982**	-3.093**	-2.694**	-1.768**
	(0.00261)	(0.00303)	(0.00544)	(0.0163)
Age	-0.0246**	-0.0252**	-0.0135**	-0.0242**
	(0.0000220)	(0.0000251)	(0.0000688)	(0.0000711)
H head	1.376**	1.480**	1.082**	1.027**
	(0.000605)	(0.000686)	(0.00169)	(0.00185)
Female	1.474**	1.417**	1.134**	2.540**
	(0.000688)	(0.000764)	(0.00188)	(0.00316)
Children	-1.629**	-1.663**	-1.057**	-2.303**
	(0.00130)	(0.00137)	(0.00500)	(0.0106)
Married	-1.193**	-1.349**	-0.642**	-0.905**
	(0.000697)	(0.000858)	(0.00177)	(0.00185)
Constant	-4.076**	-4.085**	-4.271**	-4.982**
	(0.00101)	(0.000996)	(0.00282)	(0.00382)

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

Table 35: Results, Social security and welfare assistance probability by category: Income from social security or railroad.

	(1) assist_cat	(2) assist_cat	(3) assist_cat	(4) assist_cat
Income from social security				
Citizenship	1.432**	0	0.720**	0.764**
	(0.000438)	(.)	(0.000569)	(0.000960)
HS	-0.303**	-0.507**	0.0156**	-0.164**
	(0.000257)	(0.000298)	(0.000722)	(0.00117)
Some college	-0.545**	-0.771**	0.000808	-0.256**
	(0.000266)	(0.000305)	(0.000799)	(0.00166)
College	-0.972**	-1.199**	-0.364**	-0.483**
	(0.000282)	(0.000321)	(0.000789)	(0.00254)
Advanced	-1.090**	-1.314**	-0.512**	-0.795**
	(0.000301)	(0.000340)	(0.000869)	(0.00421)
Age	0.161**	0.162**	0.168**	0.154**
	(0.00000925)	(0.00000997)	(0.0000302)	(0.0000522)
H head	0.105**	0.103**	0.116**	0.257**
	(0.000146)	(0.000155)	(0.000498)	(0.000973)
Female	0.0466**	0.0548**	0.0629**	0.147**
	(0.000137)	(0.000145)	(0.000483)	(0.000946)
Children	3.857**	3.655**	4.928**	3.178**
	(0.000696)	(0.000735)	(0.00338)	(0.00885)
Married	-0.374**	-0.375**	-0.188**	-0.211**
	(0.000155)	(0.000164)	(0.000546)	(0.00107)
Constant	-11.26**	-9.633**	-11.97**	-11.23**
	(0.000758)	(0.000718)	(0.00226)	(0.00355)

Standard errors in parentheses
+ p¡.1, * p¡0.05, ** p¡0.01

Table 36: Results, Social security and welfare assistance probability by category: Income from supplementary security.

	(1)	(2)	(3)	(4)
	assist_cat	assist_cat	assist_cat	assist_cat
Income from suppl. security				
[1em] Citizenship	1.148**	0	0.551**	0.427**
	(0.000694)	(.)	(0.000993)	(0.00210)
[1em] HS	-1.028**	-1.092**	-0.899**	-0.508**
	(0.000380)	(0.000415)	(0.00111)	(0.00248)
Some college	-1.852**	-1.941**	-1.398**	-0.830**
	(0.000474)	(0.000504)	(0.00153)	(0.00418)
College	-2.720**	-3.031**	-1.545**	-1.302**
	(0.000735)	(0.000868)	(0.00148)	(0.00733)
Advanced	-3.186**	-3.544**	-2.025**	-0.791**
	(0.00115)	(0.00143)	(0.00205)	(0.00906)
Age	0.0504**	0.0446**	0.105**	0.0739**
	(0.00000977)	(0.00000989)	(0.0000458)	(0.0000773)
[1em] H head	-0.0866**	-0.0408**	-0.0731**	-0.00713**
	(0.000361)	(0.000396)	(0.00103)	(0.00208)
[1em] Female	0.158**	0.159**	0.000529	0.398**
	(0.000310)	(0.000335)	(0.000944)	(0.00204)
[1em] Children	-1.283**	-1.534**	0.800**	0.386**
	(0.000917)	(0.000917)	(0.00669)	(0.0113)
[1em] Married	-1.527**	-1.598**	-0.983**	-0.884**
	(0.000367)	(0.000431)	(0.000945)	(0.00198)
Constant	-5.235**	-3.734**	-8.159**	-7.660**
	(0.000745)	(0.000514)	(0.00319)	(0.00449)

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

Table 37: Results, Social security and welfare assistance probability by category: Income from unemployment compensation.

	(1) assist_cat	(2) assist_cat	(3) assist_cat	(4) assist_cat
Income from unemployment compensation				
Citizenship	0.481**	0	0.293**	0.395**
	(0.000477)	(.)	(0.000867)	(0.00123)
HS	0.159**	0.212**	0.155**	-0.126**
	(0.000431)	(0.000528)	(0.00135)	(0.00122)
Some college	-0.0143**	0.0162**	0.152**	-0.0401**
	(0.000447)	(0.000537)	(0.00143)	(0.00176)
College	-0.407**	-0.376**	-0.167**	-0.624**
	(0.000499)	(0.000593)	(0.00145)	(0.00319)
Advanced	-0.858**	-0.868**	-0.441**	-0.468**
	(0.000655)	(0.000765)	(0.00168)	(0.00506)
Age	0.00968**	0.0101**	0.00785**	0.0145**
	(0.00000762)	(0.00000822)	(0.0000271)	(0.0000396)
H head	0.270**	0.275**	0.283**	0.282**
	(0.000267)	(0.000291)	(0.000862)	(0.00112)
Female	-0.456**	-0.465**	-0.317**	-0.511**
	(0.000243)	(0.000262)	(0.000821)	(0.00113)
Children	-4.242**	-4.324**	-2.724**	-3.721**
	(0.00368)	(0.00396)	(0.0108)	(0.0275)
Married	-0.318**	-0.359**	-0.168**	0.159**
	(0.000284)	(0.000311)	(0.000915)	(0.00124)
Constant	-3.772**	-3.311**	-4.002**	-4.096**
	(0.000579)	(0.000546)	(0.00159)	(0.00191)

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

Table 38: Results, Social security and welfare assistance probability by category: Income from worker's compensation.

	(1) assist_cat	(2) assist_cat	(3) assist_cat	(4) assist_cat
Income from worker's compensation				
Citizenship	0.222**	0	0.0228**	-0.0229**
	(0.00129)	(.)	(0.00255)	(0.00326)
HS	0.0350**	0.0583**	0.181**	-0.157**
	(0.00123)	(0.00155)	(0.00379)	(0.00326)
Some college	0.00259*	0.00796**	0.199**	0.124**
	(0.00126)	(0.00156)	(0.00404)	(0.00449)
College	-0.829**	-0.880**	-0.174**	-0.554**
	(0.00152)	(0.00184)	(0.00415)	(0.00831)
Advanced	-1.483**	-1.479**	-1.210**	-0.200**
	(0.00220)	(0.00253)	(0.00601)	(0.0117)
Age	0.0182**	0.0183**	0.0191**	0.0254**
	(0.0000221)	(0.0000240)	(0.0000753)	(0.000101)
H head	0.320**	0.298**	0.425**	0.476**
	(0.000774)	(0.000851)	(0.00248)	(0.00289)
Female	-0.466**	-0.469**	-0.207**	-0.751**
	(0.000719)	(0.000782)	(0.00238)	(0.00304)
Children	-2.782**	-2.769**	-2.750**	-23.12**
	(0.00626)	(0.00642)	(0.0370)	(0.00370)
Married	-0.0677**	-0.0606**	-0.213**	0.184**
	(0.000840)	(0.000927)	(0.00259)	(0.00335)
Constant	-6.138**	-5.899**	-6.586**	-6.407**
	(0.00159)	(0.00162)	(0.00484)	(0.00506)

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

Table 39: Results, Social security and welfare assistance probability by category: Income from veteran payments.

	(1)	(2)	(3)	(4)
	assist_cat	assist_cat	assist_cat	assist_cat
Income from veteran payments				
Citizenship	1.785**	0	0.945**	0.800**
	(0.00223)	(.)	(0.00300)	(0.00573)
HS	0.619**	0.472**	0.515**	0.901**
	(0.00156)	(0.00164)	(0.00639)	(0.00812)
Some College	1.306**	1.146**	1.151**	1.829**
	(0.00152)	(0.00160)	(0.00628)	(0.00841)
College	0.754**	0.590**	0.859**	2.317**
	(0.00158)	(0.00167)	(0.00623)	(0.00873)
Advanced	0.805**	0.659**	0.862**	1.459**
	(0.00164)	(0.00174)	(0.00636)	(0.0166)
Age	0.0411**	0.0420**	0.0281**	0.0491**
	(0.0000184)	(0.0000189)	(0.0000965)	(0.000234)
H head	0.188**	0.193**	0.218**	0.0489**
	(0.000578)	(0.000598)	(0.00259)	(0.00587)
Female	-1.750**	-1.765**	-1.540**	-0.834**
	(0.000706)	(0.000730)	(0.00319)	(0.00619)
Children	-2.244**	-2.541**	0.0143	-21.75**
	(0.00772)	(0.00838)	(0.0209)	(0.00821)
Married	-0.142**	-0.126**	0.0221**	-0.466**
	(0.000648)	(0.000669)	(0.00317)	(0.00612)
Constant	-8.757**	-6.823**	-8.200**	-9.640**
	(0.00255)	(0.00162)	(0.00716)	(0.0117)

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

Table 40: Results, Social security and welfare assistance probability by category: Income from survivors benefits.

	(1)	(2)	(3)	(4)
	assist_cat	assist_cat	assist_cat	assist_cat
Income from survivors benefits				
Citizenship	1.400**	0	0.466**	0.493**
	(0.00233)	(.)	(0.00327)	(0.00723)
HS	0.110**	-0.0808**	0.734**	0.586**
	(0.00139)	(0.00148)	(0.00500)	(0.00812)
Some college	0.185**	-0.00397**	0.644**	0.611**
	(0.00140)	(0.00148)	(0.00557)	(0.00985)
College	0.242**	0.0749**	0.659**	-0.107**
	(0.00143)	(0.00152)	(0.00532)	(0.0177)
Advanced	0.325**	0.157**	0.748**	-23.30**
	(0.00150)	(0.00159)	(0.00568)	(0.00592)
Age	0.0716**	0.0716**	0.0807**	0.0845**
	(0.0000222)	(0.0000230)	(0.000108)	(0.000243)
H head	0.154**	0.148**	0.310**	0.143**
	(0.000714)	(0.000742)	(0.00309)	(0.00708)
Female	0.613**	0.605**	0.850**	0.953**
	(0.000679)	(0.000700)	(0.00323)	(0.00749)
Children	0.807**	0.611**	2.014**	0.572**
	(0.00252)	(0.00259)	(0.0133)	(0.0419)
Married	-1.292**	-1.231**	-1.840**	-2.262**
	(0.000700)	(0.000728)	(0.00307)	(0.00820)
Constant	-10.09**	-8.483**	-10.94**	-11.14**
	(0.00265)	(0.00187)	(0.00864)	(0.0160)

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

Table 41: Results, Social security and welfare assistance probability by category: Income from disability.

	(1)	(2)	(3)	(4)
	assist_cat	assist_cat	assist_cat	assist_cat
Income from disability				
Citizenship	0.799**	0	0.370**	0.228**
	(0.00147)	(.)	(0.00252)	(0.00365)
HS	-0.203**	-0.297**	-0.0480**	-0.115**
	(0.00108)	(0.00120)	(0.00379)	(0.00392)
Some college	-0.258**	-0.376**	0.156**	-0.0255**
	(0.00110)	(0.00121)	(0.00395)	(0.00561)
College	-0.662**	-0.798**	0.0216**	-0.740**
	(0.00123)	(0.00136)	(0.00393)	(0.0105)
Advanced	-0.829**	-0.976**	-0.0773**	-0.909**
	(0.00147)	(0.00161)	(0.00437)	(0.0184)
Age	0.0404**	0.0412**	0.0356**	0.0557**
	(0.0000187)	(0.0000197)	(0.0000725)	(0.000116)
H head	0.163**	0.191**	-0.0541**	0.0949**
	(0.000657)	(0.000700)	(0.00243)	(0.00337)
Female	0.00822**	0.000568	0.306**	-0.287**
	(0.000620)	(0.000656)	(0.00237)	(0.00338)
Children	-1.907**	-1.985**	-22.55**	-0.742**
	(0.00411)	(0.00416)	(0.00368)	(0.0314)
Married	-0.471**	-0.477**	-0.419**	-0.112**
	(0.000679)	(0.000727)	(0.00241)	(0.00359)
Constant	-7.254**	-6.359**	-7.500**	-8.028**
	(0.00165)	(0.00133)	(0.00451)	(0.00667)

Standard errors in parentheses
+ p¡.1, * p¡0.05, ** p¡0.01

Table 42: Results, Social security and welfare assistance probability by category: Income from educational assistance.

	(1)	(2)	(3)	(4)
	assist_cat	assist_cat	assist_cat	assist_cat
Income from educational assistance				
Citizenship	0.236**	0	0.0219**	0.434**
	(0.000466)	(.)	(0.000776)	(0.00209)
HS	1.887**	1.913**	1.803**	1.000**
	(0.00116)	(0.00127)	(0.00393)	(0.00444)
Some college	3.614**	3.611**	3.537**	3.315**
	(0.00114)	(0.00125)	(0.00380)	(0.00400)
College	3.117**	3.117**	2.954**	2.934**
	(0.00116)	(0.00128)	(0.00387)	(0.00486)
Advanced	3.360**	3.327**	3.325**	3.131**
	(0.00122)	(0.00134)	(0.00392)	(0.00678)
Age	-0.113**	-0.113**	-0.107**	-0.115**
	(0.0000192)	(0.0000203)	(0.0000605)	(0.000172)
H head	0.0191**	0.0103**	0.0937**	0.0298**
	(0.000305)	(0.000326)	(0.000942)	(0.00228)
Female	0.334**	0.349**	0.171**	0.524**
	(0.000229)	(0.000242)	(0.000758)	(0.00198)
Children	-1.763**	-1.740**	-2.217**	-6.108**
	(0.00139)	(0.00145)	(0.00685)	(0.0871)
Married	-0.586**	-0.553**	-0.808**	-0.659**
	(0.000312)	(0.000334)	(0.000945)	(0.00229)
Constant	-2.603**	-2.363**	-2.417**	-2.766**
	(0.00125)	(0.00131)	(0.00397)	(0.00550)

Standard errors in parentheses

+ p¡.1, * p¡0.05, ** p¡0.01

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