Taking One for the Team: Shocks at Destination and Households' Supply of Migrants*

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Abstract

We study how migration decisions of Mexican households respond to unemployment shocks in the U.S. We emphasize the role played by households (as opposed to individuals) as the decision-making units at origin. We show that Mexican families with members working abroad (exposed families) respond to negative economic shocks in the U.S. in a heterogeneous fashion. Poor families react by sending additional members, while richer families respond by returning their members. We argue that this heterogeneous response is driven by the relative magnitudes of income and substitution effects after a negative shock in the U.S. While the income effect dominates the substitution one for poor households, the opposite holds for richer households. These results are also informative to the literature on selection patterns in international migration, suggesting a new channel through which negative shocks in the host economy affect negatively the skill composition of subsequent migrants.

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1 Introduction

While migration flows from Mexico to the United States have traditionally responded to the economic conditions in both countries, this relationship appears to have weakened in recent years, which have been characterized by sustained migration in the presence of a relative worsening of the U.S. economic conditions to those in Mexico.[1] Furthermore, existing theoretical models, where the level of relative skill prices is the main determinant of migrant selection, cannot account for the skill composition of recent Mexican migrants to the U.S. (Borjas and Friedberg 2009).

This paper addresses two main questions: i) why do we continue to observe sustained migratory movements to traditional host countries even when these countries experience a relative worsening in economic conditions? and ii) what is the skill composition of the migrants that continue to move to such destinations? To that end, we develop and successfully test a simple model of migration in which the decision making unit is the family, instead of the individual. We show that, in a context of high past migration,[2] where remittances are an important component of the income of the household members that remain at origin,[3] economic shocks at destination may have a non-trivial impact on subsequent migration flows and their skill composition.

The literature on migration has broadly focused on understanding how economic performance at origin and destination countries shapes migratory movements. A strand of this research attempts to explain observed cross-country migration patterns (Docquier, Lowell, and Marfouk 2009; Grogger and Hanson 2011). Other studies, using more disaggregated data, explore how changes in economic conditions and labor market outcomes at destination affect migrants' decisions to return to their origin country (Borjas 1989; Borjas and Bratsberg 1996; Dustmann 2003; Yang 2006). A common element to this literature is that, explicitly or implicitly, it focuses on the individual as the decision-making unit for migration decisions. Our paper departs from this literature by theoretically considering households at origin as the decision-making units for migratory decisions and by empirically analyzing the way in which families with migrants cope with labor market shocks at destination.

[1]Focusing on the 1990-2010 period, a regression of the change in the log of Mexican immigrants entering the United States (according to data from the PEW research center) against GDP growth in both countries (taken from the World Bank data series) shows a positive (negative) and significant relationship between US (Mexico) GDP growth and changes in migration flows. However, the coefficients are close to and insignificantly different from zero for the 2005-2010 period.

[2]According to Passel, Cohn, and González-Barrera (2012), the number of Mexican born individuals living in the United States has more than doubled in the last two decades (from 4.5 million in 1990 to more than 12 million in 2010).

[3]Mexico's income from remittances has increased from 3.6 billion to 21.3 billion USD between 1995 and 2010. Source: www.banxico.org.mx.

The main intuition behind our model and our results is that, for the Mexican case, in which a large number of households have at least one member residing in the United States, employment shocks at destination may have a direct impact on Mexican households' income, thus affecting their migration decisions in a non-trivial way. Poor Mexican households optimally respond to a negative economic shock at their traditional destination by increasing their number of migrants. This happens since the income effect resulting from the decrease in remittances outweighs the substitution effect that makes the U.S. labor market relatively less attractive than the Mexican one.[4]

Using a unique dataset that allows us to construct an origin-destination matrix from Mexican municipalities to the main destination cities within the United States, we construct time-varying measures of expected unemployment at destination for each municipality in our sample (given the geographical pattern of past migration). We then explore their relationship with migration flows between 2005 and 2010 that we construct using the 2010 Mexican Census. In line with the predictions of our model, results show that Mexican families with members working abroad (exposed families) respond to negative unemployment shocks in the U.S. in a heterogeneous fashion. By dividing our sample by quintiles according to their domestic labor income, we observe that higher income families adjust by bringing their members back, while lower income families send more workers to the U.S. labor market. Additionally, the response of non-exposed families (those without members working in the U.S.) is weak or nonexistent.

In our empirical exercise, we address a number of concerns regarding the robustness of our results. The differential response of households across different income levels is robust to considering predicted –instead of realized– domestic labor income and to splitting the sample by education quintile of adults, thus addressing the concern that our measure of domestic income (measured in 2010) is itself affected by past migration. Our results also hold when we restrict to the sample to Mexican municipalities for which there is more precise information on the geographical distribution of past migrants in the U.S.. Further robustness checks show that our estimates neither change when we control for past migration of different income groups in the municipality of origin, nor when we account for varying border enforcement in different points of the frontier, which might be correlated with local labor market conditions in the U.S. We also deal with the concern that economic shocks in the U.S. might be correlated with other unobserved municipality-specific shocks by including municipality-year fixed effects. Finally, we show additional robustness checks that deal with some limitations presented by the data on migration that comes from the 2010 Mexican Census.

[4] Nekoei (2013) documents that labor market supply decisions of migrants in the U.S. are very responsive to income shocks originated by changes in real exchange rates.

In our baseline analysis, we abstract from the possibility that economic shocks in the U.S. could be heterogeneous across income levels. That is, we assume that all households from a given Mexican municipality are subject to the same change in expected unemployment in the U.S. Nonetheless, our results remain unchanged when we relax this assumption. To do so, we first exploit variation in the industry composition of Mexican immigrants in the U.S. labor market across income levels.[5] We also consider the possibility that, within a given Mexican municipality, poorer and richer individuals migrate to different US cities. We then compute quintile-specific origin-destination matrices, and find that our results are robust to accounting for heterogeneous shocks across income quintiles. Although throughout the paper we abstract from the fact that moving costs may vary along the income distribution, we discuss the implications that such costs may have for our analysis and argue that they cannot account for our host of results.

Our findings are informative to the literature that relates economic conditions and migration flows. We show how negative labor market shocks at destination interact with previous migration, thus impacting the income of households at origin in a way that may increase migration for specific subpopulations. This is especially relevant for countries with high levels of migration. For the specific case of Mexico, this contributes to explain the persistent migration of Mexicans to the U.S. even in the midst of a strong recession in the latter country.

This paper also has implications for the literature that tries to predict the nature of the selection of migrants from Mexico to the U.S. (Borjas 1987, 1994; Caponi 2006; Chiquiar and Hanson 2005; Fernández-Huertas Moraga 2013). Departing from a simple model that predicts negative selection in the absence of remittances, our results suggest that labor market shocks at destination have a non-trivial effect on the skill distribution of the migrant population. In particular, negative shocks drive migrants from high-skilled households back to origin, while increasing the number of migrants from low-skilled families, which contributes to the negative selection of Mexican migrants to the U.S.[6]

The literature has traditionally focused on the differential in expected wages (and the monetary costs of migrating) as the determinants of migration patterns. We, in turn, highlight the importance of the effect that wages at destination have on households' income at origin, which vary across income and skill levels. Our results show that, to understand the composition of current migratory waves, one should consider the interaction between past migration patterns and contemporary economic shocks at

[5]Poor and rich Mexican immigrants work in different industries in the U.S.

[6]In our empirical analysis we proxy household skill by the the average years of education of all household adults.

destination. To our understanding, this mechanism has been previously ignored.

We are not the first ones to highlight the importance of considering the family as the decision-making unit in the migration literature. Borjas and Bronars (1991) present evidence that is consistent with an economic model of family migration, if immigrants are negatively selected. However, the literature that followed Borjas and Bronars (1991) has largely ignored the role played by households at origin in migratory decisions, possibly due to data availability issues.

The rest of the paper is as follows. Section 2 reviews the existing literature, stressing the novelty of our approach. In section 3, we briefly describe the setting for which the empirical analysis is performed, by presenting some historical and current patterns of Mexican migration to the U.S. Section 4 introduces our theoretical framework. We present our data and empirical specifications in section 5. We introduce our main results in section 6, and perform a series of robustness checks in section 7. In section 8 we explore whether alternative mechanisms are able to account for our results. Section 9 concludes.

2 Existing Literature

There is a large literature on the determinants of migration patterns across countries. Several studies measure the relevance of economic variables at both the origin and destination countries (push and pull factors, respectively) in shaping cross-country migratory flows (Clark, Hatton, and Williamson 2007; Docquier, Lowell, and Marfouk 2009; Grogger and Hanson 2011; Mayda 2010).

Using household or individual level data from specific countries, several authors study migration and return decisions within life-cycle residential location models (Borjas and Bratsberg 1996; Dustmann 2003; Yang 2006). The focus of these models is on whether, due to adjustments in income expectations or economic shocks at destination, individual migrants stay at destination permanently or they return to their origin, as well as on their optimal return time. In particular, Kennan and Walker (2011) develop a structural dynamic model of migration over many locations to explain interstate movements in the U.S. Similar structural approaches have been applied to the case of the Mexican migration to the U.S., with a special interest in capturing dynamics specific to illegal immigrants (Lessem 2013). The counterfactual exercises of these studies show that a relative increase of wages in Mexico spurs the return of migrants to Mexico. Our paper differs from most of the literature by focusing on how migration decisions are optimally taken to maximize household –instead of individual–income, which leads to distinct predictions about how individuals move when facing changing economic conditions in the destination labor market.

An aspect of migration that has received special attention in the literature is that of the selection and skill composition of migrants. The income maximization framework of Roy (1951) is the usual starting point for these papers. First applied to explain migration patterns by Borjas (1987), one of its main implications is that migrants should be negatively selected from the skill distribution when the earnings inequality at the origin country is larger than at destination. For the specific case of Mexico and the U.S., this framework led to the hypothesis that Mexican migrants should be negatively selected, since the U.S. offers higher wages for low-skilled workers and relatively lower returns to skills. However, the empirical literature that tests this implication for the U.S.-Mexican case provides mixed evidence.[7] Other empirical studies document the evolution of selection patterns over time (Aguilar Esteva 2013; Borjas and Friedberg 2009).

Recent contributions (Angelucci 2013; McKenzie and Rapoport 2010) provide arguments that to some extent reconcile the negative selection hypothesis and the diverse empirical results. In particular, they suggest that financial constraints prevent low-income Mexicans from migrating. Relaxing such constraints (e.g., via network effects or conditional transfer programs) allows for greater levels of migration, especially from the bottom of the skill distribution, impacting the overall skill composition of migrants. We, in turn, suggest that the differences in migration costs across skill levels may not be the only forces explaining the observed selection patterns and their evolution over time. In particular, abstracting from the monetary costs of migration, our framework emphasizes how the interaction between contemporary economic shocks at destination and past migration may affect the skill composition of the current migrants. Our differential results on skill levels show that negative shocks in the U.S. are associated with more negative selection of new migrants.

This paper also complements the literature that tests the impact of economic conditions in Mexico on migration patterns (Monras 2013; Munshi 2003; Paulson 2000), and to the one that studies the impact of migration on the destination's economic outcomes (Borjas 2003; Card 1990, 2001; Friedberg and Hunt 1995; Manacorda, Manning, and Wadsworth 2012; Ottaviano and Peri 2012). We propose, instead, a novel empirical approach that focuses on the origin household as the decision making unit to understand how families cope with changing economic conditions at destination. Underlying our model is the role played by remittances as a mechanism through which migrants share their labor income with origin households, a phenomenon that has been studied in the

[7] See, among others, Caponi 2006; Chiquiar and Hanson 2005; Fernández-Huertas Moraga 2013.

Mexican and other contexts (see, among others, Amuedo-Dorantes, Bansak, and Pozo 2005; Paulson 2000; Yang 2011).

Finally, by focusing on the household as the unit of migratory decisions, our framework allows us to relate the literature on the determinants of migration to the existing theoretical and empirical evidence on "added worker effect". This particular literature studies the response of secondary workers to unemployment shocks experienced by the primary worker of the household (Attanasio, Low, and Sánchez-Marcos 2005; Basu, Genicot, and Stiglitz 1999; Lundberg 1985; Parker and Skoufias 2004; Stephens 2002), generally suggesting that secondary workers may have negative labor supply elasticities at low wage rates and positive ones at higher rates (Dessing 2002). Our results, related to migratory movements, match very well these observations. We are, to our knowledge, the first to link these findings on household labor supply with the migratory phenomenon.

3 Mexican Migration to the U.S.

3.1 Migration Flows

The movement of Mexican workers to the U.S. is a historical phenomenon with large impacts on the demographic dynamics of both countries. The first important flow of Mexican laborers to the U.S. began in the early 20$^{\text{th}}$ century with the curtailment of Japanese immigration and the advent of World War I, during which American workers went to fight overseas and Mexicans laborers filled in for them. The onset of World War II led to the agreement of the Braceros program between the governments of the U.S. and Mexico. The Braceros program was intended to supply US growers with Mexican labor through legal channels. However, American farmers regularly recruited undocumented workers as their demand for labor was not met by the number of immigrants entering legally through the program. The Immigration and Nationality Act of 1965 brought major changes to the U.S. immigration policy. Although the act did not relax rules on immigration coming from Latin America, it was followed by a steep increase in the number of immigrants from the region, especially from Mexico. The Bracero program, through which many Mexican workers had entered the U.S. in the previous decades, was eliminated. Consequently, an increasing fraction of the new immigrants were illegal.

In the last two decades, migration flows can be divided into three distinct periods, as suggested by Chiquiar and Salcedo (2013). During the 1990s, with the ratification of the North American Free Trade Agreement (NAFTA), the number of Mexicans going to the U.S. was high and increasing, which the authors attribute mainly to Mexico's poor economic performance. This led to the largest decade-to-decade increase in the number of Mexican-born residing in the U.S., as Table C1 in the Appendix shows. Between 2000 and 2007, those flows came to a standstill, possibly reflecting the stricter immigration policy practiced by the U.S. after the 9/11 terrorist attacks. Finally, since the global economic crisis, the number of Mexicans leaving for the U.S. started to decrease, with annual flows averaging fewer than 200,000 people. Passel, Cohn, and González-Barrera (2012) state that "while it is not possible to say so with certainty, the trend lines within this latest five-year period suggest that return flow to Mexico probably exceeded the inflow from Mexico during the past year or two". This means that, during the period of our study –in which the global crisis affected the U.S. more strongly than Mexico– net migration from the U.S. to Mexico was close to neutral or, at most, only slightly negative.

Over the decades, Mexican immigrants have constructed social networks at their traditional destinations, which play an important role in improving immigrants' labor market outcomes by substantially reducing information failures (Munshi 2003). We exploit the fact that, since different Mexican communities have traditionally migrated to different destinations, economic shocks that affect different US regions in a heterogeneous fashion should then imply differential migration responses across Mexican municipalities.

3.2 Geographic Location

Mexican-born individuals are spatially distributed across the whole US territory. California, Texas, Illinois and Arizona are the four states that have received the most Mexican immigrants. Table C2 in the Appendix ranks the top ten US Metropolitan Areas according to the share of the Mexican-born population living in them as of 2010. Four of those ten MA's are located in California, three in Texas, one in Arizona, and the remaining two are the Chicago MA (which expands through Illinois, Indiana and Wisconsin) and the New York MA (expanding through New York, New Jersey and Pennsylvania). Those ten MA's accounted for almost half of the Mexican-born residing in the U.S. in 2010. Other important MA's are Atlanta, Georgia (1.59% of the total Mexican-born population), Las Vegas, Nevada (1.50%), and Denver, Colorado (1.24%). The final column in Table C2 shows the proportion of each of these MA's population that was Mexican-born as of 2005. While the ranking changes considerably, the Mexican born population is also a larger share of the total population in Southern states, with the Los Angeles-Long Beach-Santa Ana Metro Area showing the highest value for this variable (14.9%). On the other hand, only 1.3% of the residents on the New

York-Northern New Jersey-Long Island Metro Area were Mexican born by 2005.

Additionally, during the period of our study, we observe great heterogeneity in economic performance across US cities. For example, between December 2005 and December 2010, Florida, Nevada and California experienced unemployment increases of over 7%, while some states had more modest losses in employment (under a 1% increase in North Dakota, Alaska and Nebraska, for example). This paper is among the first to exploit that this feature of the U.S. economy, together with the location of traditional immigrant networks, translates into considerable variation in the expected economic conditions at destination for individuals residing in different municipalities of Mexico.

4 Theoretical Framework

We develop a simple theoretical model of household migration decisions to understand how households at origin that have household members at destination reoptimize their migration decisions when they face unemployment shocks at destination. Our aim is not to provide a theoretical contribution but simply to guide our empirical exercise. Following Roy (1951) framework and previous work on the Mexico-US migration literature, we consider that households face wage equations of the following form:

$$w_{mex} = \mu_{mex} + \delta_{mex} \cdot s$$

$$w_{us} = \mu_{us} + \delta_{us} \cdot s$$

where w_i is wage in country i, μ_i is the baseline wage for uneducated workers in country i and δ_i represents the returns on schooling. The literature stresses the fact that minimum wages are higher in the U.S. and returns to schooling are greater in Mexico, which in our framework translates to $\mu_{mex} < \mu_{us}$ and $\delta_{mex} > \delta_{us}$ (McKenzie and Rapoport 2010). Defining $\mu_{mig} = \mu_{us} - \mu_{mex} > 0$ and $\delta_{mig} = \delta_{mex} - \delta_{us} > 0$, we have that the migration premium for an individual with skill level s can be expressed as:

$$w_{mig} = \mu_{mig} - \delta_{mig} \cdot s$$

It is straightforward to see that, since the benefits from migration are decreasing in s, there exists a maximum skill level s^{max} up to which migrating is beneficial. This creates the negative selection on skills hypothesized by the literature.

We assume that all members of a family have the same skill level, s. Households maximize a Cobb-Douglas utility function, whose arguments are consumption c and the amount of members that remain in Mexico, d. This implies the reasonable assumption that families have a preference for having their members at home. We treat both c and d as continuous variables for simplicity. Households are required to meet a minimum level of consumption, $\underline{c}$ and to maintain a minimum amount of household members in Mexico, $\underline{d}$. The inclusion of the minimum consumption level $\underline{c}$ is important to understand the migrant supply function of families at very low wage levels. In particular, its introduction in the utility function predicts that at low enough wage levels, the migrant supply elasticity of households will become negative. The inclusion of the minimum number of household members in Mexico $\underline{d}$ relates to the fact that in our data we cannot observe those Mexican households that move entirely to the U.S.

For simplicity, we abstract from (potentially heterogeneous) costs of moving. While the literature has emphasized the potential importance of moving costs to explain the composition of migration flows (Angelucci 2013; McKenzie and Rapoport 2010), these are secondary to our analysis. In Section 8.2 we present a brief discussion of the implications of incorporating heterogeneous moving costs into our framework and argue that these cannot account for the host of our empirical results.

We do not model the household decision in terms of labor and leisure, but only their decision to distribute labor between domestic and foreign labor markets. We also normalize the price of the consumption good to 1. Given this, households optimally choose the quantity of labor supplied in the U.S. solving the following maximization problem:

$$max_{c,d}\left\{(c-\underline{c})^{\alpha}(d-\underline{d})^{\beta}\right\}$$

$$s.t.\ X = d\cdot(\mu_{mig}-\delta_{mig}\cdot s)+c$$

$X = \bar{m}\cdot(\mu_{mig}-\delta_{mig}\cdot s)+D(s)$ is income that a household would earn if it sends all its members to work to the U.S., where $\bar{m}$ is the total amount of labor that a family can supply and $D(s)$ is domestic labor income corresponding to a family with skill level s, with $D'(s) > 0$. We further assume $\alpha+\beta = 1$.

Assuming an interior solution, the first order conditions yield

$$c^* = \underline{c}+\alpha\cdot(X-\underline{d}\cdot(\mu_{mig}-\delta_{mig}\cdot s)-\underline{c})$$

and

$$d^* = \underline{d}+\frac{1-\alpha}{\mu_{mig}-\delta_{mig}\cdot s}\cdot((\bar{m}-\underline{d})\cdot(\mu_{mig}-\delta_{mig}\cdot s)+D(s)-\underline{c}),$$

or equivalently, the optimal migration of a household with skill level s is given by

$$m^* = \bar{m} - \underline{d} - \frac{1-\alpha}{\mu_{mig} - \delta_{mig} \cdot s} \cdot ((\bar{m} - \underline{d}) \cdot (\mu_{mig} - \delta_{mig} \cdot s) + D(s) - \underline{c}),$$

The main goal of this simple framework is to illustrate how m^* of families with $m^* > 0$ responds to changes in foreign wages and, in particular, how this response may vary with skill levels. For this reason, we focus the analysis on shocks to μ_{mig}, meaning that the effect is equal across all levels of s, while returns to skill remain unchanged.[8] We have that:

$$\frac{\partial m^*}{\partial \mu_{mig}} = \frac{1-\alpha}{(\mu_{mig} - \delta_{mig} \cdot s)^2} \cdot (D(s) - \underline{c}) \tag{1}$$

The sign of the derivative in (1) depends on the value of $D(s)$ with respect to $\underline{c}$. On the one hand, if the household has a sufficiently high level of domestic labor income, the derivative has a positive sign. On the other hand, for households with low levels of s, meaning low levels of domestic wages, the derivative is negative. That is, for low domestic income families, negative shocks in the U.S. are followed by an increase in the amount of individuals that leaves the household to supply further labor in the foreign market.

Moreover, this model also predicts that, for those households with $D(s) > \underline{c}$ (negative derivative) the absolute value of the derivative is increasing in s, as the numerator grows and, since we are focus on families with positive migration, the denominator tends to zero. Thus, for high-domestic income families, a negative shock in the U.S. is followed by return migration, and this adjustment is stronger the higher the domestic income of the household.

After a negative foreign shock, the U.S. labor market becomes relatively less attractive, triggering a substitution effect that pushes all families to reduce the amount of labor they supply in the U.S. However, the reduction in foreign wages also makes families with migrants poorer, and this gives rise to an income effect which leads to greater levels of migration (since domestic labor is a normal good). The difference in the relative magnitudes of these two effects is what drives the heterogeneity in the observed responses to the shocks. For low domestic income families the latter effect dominates, as the decrease in foreign labor income impacts their total budget in a way that jeopardizes their ability to meet the required minimum levels of consumption. Contrarily, for higher income families, the income effect is more moderate and the substitution effect becomes dominant, leading them to substitute foreign for domestic work after the migration

[8]The message we want to convey with this model is that the sign of the response of families to shocks at destination will depend on the income level of the household. In section 5.2 we address the implications of the assumption of homogeneous shocks across skill levels.

premium diminishes.[9]

This simple model helps us to illustrate that households with different income levels may react differently to an economic shock of a given magnitude at the destination. However, while our model assumes that the intensity of the shock is the same for all households irrespective of their income level, there is the possibility that it differs. In section 8.1., we deal with the possibility that our empirical test of the model's implications is confounded by heterogeneity in the magnitude of the shock across income/skill levels.

Finally, although our theoretical framework discusses wage changes, throughout our empirical work we use changes in employment levels instead of wages. Some authors have documented the fact that the period we are studying has been characterized by nominal wage rigidity in the U.S., even during moments with very high levels of job destruction.[10] Given this, relative magnitudes of local labor demand shocks are better captured by changes in employment. Alternatively, we could redefine wage w_i as the expected wage, which is a function of the wage conditional on being employed, W_i , times the probability of being employed, p_i. In this redefined framework, our empirical work would be capturing changes in p_i.

5 Data and Methodology

5.1 Data

We obtain data from several sources. We use survey data from the 1999 to 2003 waves of the EMIF Norte (Survey on Migration at the Mexican Northern Border).This survey is conducted annually by the Mexican Northern Border College in association with several government agencies. During these years, interviews were conducted in seven Mexican cities: Matamoros, Nuevo Laredo, Piedras Negras, Ciudad Juárez, Nogales, Mexicali and Tijuana, which span the entire US border. Respondents are asked in which Mexican city they were residing, whether they were planning to cross into the U.S., and which city was their final destination in the U.S. Our subsample consists of all those individuals intending to cross the border for which both the municipality of residence in Mexico and the desired American destination are known. There is at least one migrant for 1,206 municipalities, which are about half of all total Mexican

[9]Additionally, s^{max} is reduced after a decrease in μ_{mig}, meaning that the most skilled families among those who found optimal to send members abroad before the shock, find optimal to have no migrant workers after the shock. In other words, they switch from an interior solution to a corner one. This reinforces the negative effect on migration for richer households that we previously described.

[10]See Cadena and Kovak (2013) for a discussion on this issue.

municipalities. For the average Mexican municipality in our sample, we observe 9.84 migrants. We have a total of 12,012 observations.[11]

Figure 1 presents the distribution of municipalities by the number of migrants observed in the EMIF. As a robustness check, we focus on those municipalities with more information on the geographical distribution of past migrants in the U.S. by restricting our sample to those with 10 or more migrants (269 municipalities meet this criteria). Accordingly, we divide Figure 1 in two panels: the top panel contains all the municipalities with at least one migrant in the EMIF, while the bottom panel includes the restricted sample of municipalities with 10 or more migrants in the EMIF.[12]

With this information we construct origin-destination cells that capture Mexican municipality-specific measures of the geographical distribution of migrants in the U.S. For each origin-destination cell, we compute:

$$p_{m,d} = \frac{N_{m,d}}{\sum_{d=1}^{D} N_{m,d}}$$

where $N_{m,d}$ is the number of migrants from Mexican municipality m to destination d, and the denominator is the total number of migrants from m. For each m, $p_{m,d}$ is our measure of the municipality-specific geographical distribution.[13]

We estimate the external shock received by households of municipality m as a weighted average of the shocks experienced at the American destinations, using $p_{m,d}$ as the weight for each destination. In particular, we use unemployment data at the Metropolitan Area level for December of each year between 2005 and 2010 from the U.S. Department of Labor[14], and estimate the economic shock received by municipality m in year t as the change on unemployment, according to the formula:

$$S_{m,t} = \sum_{d=1}^{D} p_{m,d} * \Delta unemployment\_rate_{d,t}.$$

Notice that, while our measure of geographical distribution, $p_{m,d}$, is constant over time,

[11]We focus on the data from the 1999 to 2003 waves for several reasons. First the data from 2005 might be affected by the unemployment changes whose effect we study. Second, there was change in the coding of destinations in the U.S. in 2004, which led us to drop the 2004 data for the sake of consistency in the coding. Third, data prior to the 1999 is probably less accurate to reflect the more contemporary location of Mexican migrants from a municipality in a destination in the U.S. Addition, before 1999 the data was reported biannually, which led us to doubt whether there were also changes in the methodology used to collect the data.

[12]For better visualization, we exclude from this Figure 12 municipalities that have more than 100 migrants

[13]Due to data limitations, we abstract from the possibility of relocation by Mexican immigrants within the U.S.

[14]In an alternative specification, we use Mexican-born (instead of overall) unemployment data at the same geographical level. See Section 7.2 for more detail.

our municipality-year specific shocks are time-varying.

The fact that the weights $p_{m,d}$ are constructed from relatively few observations of past migrants introduces some noise in our measure of the foreign unemployment shock received by Mexican municipalities. In section 5.2 we discuss the implications of this issue for our empirical exercise, and how we address it.

Figure 2 shows the estimated unemployment rate at destination for all municipalities in our sample in 2005. Municipalities in our sample are distributed across the whole Mexican territory, and there is significant variation in municipal unemployment levels. Figure 3 illustrates the change in unemployment rate between 2005 and 2006, showing that there is even more within municipal variation in unemployment changes, which we exploit in our strategy, than in the municipal levels in 2005.

Figure 4 presents the distribution of changes in expected unemployment rates pooling all Mexican municipalities and years in our sample. The range of such changes goes from a 2% decrease to a 4% increase. Overall, 62% of the changes throughout our sample are positive (unemployment increases). However, this variation is somewhat reduced when we consider the within-year variation. From 2008 on, when most of the action in our sample takes place, almost all of the expected unemployment changes received by Mexican households have positive sign. Consequently, we consider that our results are specially informative for a situation of increasing unemployment at destination.

Our migration data comes from the 2010 Mexican Census. In the Census, households provide retrospective information on migration for individuals who were living in that household in June 2005, and moved to the U.S. after that date. Therefore, the definition of migrant we use in this paper, corresponding to that of the Mexican census, is an individual who left her Mexican household and went to the U.S. after June 2005, irrespective of whether she remained abroad or not. For migrants, the year of the most recent trip to the U.S. is reported, as well as the year of the returning trip if she returned. Unfortunately, the Census does not provide information on the purpose of the trip, so we consider all movements to be work-related. This assumption is not far-fetched, as it has been documented that a very large share of Mexican migration to the U.S. is for work-related reasons.[15] We use this information on migration to construct a panel at the household level with yearly information on migration events to and from the U.S.[16]

From this data on migration we also construct an indicator variable, *exposed*, to capture

[15] Angelucci (2013)) estimates from a sample of 506 Mexican villages that the share of international migration that was work-related in 1998 was 85%.

[16] See the Data Appendix for an exhaustive discussion of some data issues.

whether a household has members living in the U.S. at the beginning of year t. Notice that exposed is time-varying. We use such within-household variation to identify the differential response to shocks at destination of families that have migrants in the U.S. relative to those that do not.

Our migration data presents two main shortcomings, which we explain further in Appendix A and illustrate in Figures A1 and A2. First, the Census only asked about the last trip of an individual. Therefore, as indicated in Figure A1, if a person has multiple trips to the U.S. in the period we study, we introduce two potential sources of measurement error: we miss the information regarding prior migration events of the individual, and potentially miss-code the individual's household as non-exposed during the years the individual returns to Mexico.[17] Second, for those individuals who left to the U.S. before June 2005 and returned to Mexico during the period we analyze (*pre-2005 migrants*), the date of the return trip is missing in the Mexican Census. In our baseline regressions, we i) assume that each individual had no more than one migration spell during the 2005-2010 period, and ii) exclude households with *pre-2005 migrants*. However, in section 7.3, we present two empirical strategies that partially deal with these two issues and show that results are robust to these alternative specifications.

Once we match the migration data, which comes from the 2010 Mexican census, with the information on unemployment at destination, we end up with a final sample of 1,279,542 households from 1,206 municipalities (roughly half of all Mexican municipalities). For each household we have one observation per year for six years.

Throughout our empirical analysis, we show results dividing our sample by income quintiles. Table 1 reports descriptive statistics following that criterion. Panel A focuses on our full sample, which consists of just over one million Mexican households to which the migration module was administered to during the 2010 Mexican Census and that belong to municipalities captured by the EMIF. Panel A indicates that the average member of the highest quintile receives an income almost 20 times larger than that of the average member of the lowest quintile. For the lowest earning group, average domestic labor income in 2010 was 1,150 Mexican pesos (roughly 90 US$/month). Predicted labor income shows much less dispersion. Also, predicted labor income is very similar for the two lowest quintiles, which reflects the fact that observable predetermined characteristics are not very informative about realized labor income for those in the bottom of the earnings distribution. Schooling levels are, as expected, increasing with income level. The average years of education of household heads in the lowest income quintile (5.2) are half of those for household heads in the highest income quintile (10.4). Also, household heads in the lowest income quintile are slightly older

[17] If the individual has additionally household members in the United States, the household is correctly coded as exposed

than in the rest of the sample.

Panel B of Table 1 focuses on the households that change their exposure status at least once during the sample period is 31,558 (2.47%). These households are distributed along the entire income distribution, although slightly concentrated at the two bottom quintiles. As detailed in the Appendix, this figure represents an underestimate since, due to data limitations, we cannot capture those households that fully moved to the U.S. and those households with individuals who moved before 2005 but return between 2005 and 2010, since the return date is not reported.[18] However, despite the fact that our measure of exposed is understated, it is fairly consistent with the number of Mexican households that receive remittances from the U.S. (CONAPO 2005). The values of the variables for the households with changing exposure status are within the ranges of the general population, although they are one average somewhat less educated and have lower income than the mean household of each quintile.

In Table 2 we compare the observable characteristics of the EMIF migrants with those of the adults of the the households that change their exposure status in the 2010 Mexican Census.[19] Migrants in the EMIF are not too different from the adults in households with migrants captured by the census. The migrants in the EMIF are few years younger, reflecting that older household members are relatively less likely to move. In line with this, EMIF migrants have slightly lower labor income (from their previous job) and have around 0.7 years more of education on average, probably corresponding to the fact that they come from younger –generally more educated– cohorts.

5.2 Methodology

Our baseline specification is:

$$Y_{imst} = \alpha + \delta \cdot exposed_{it} + \beta_0 \cdot shock_{mt-1} + \beta_1 \cdot (exposed_{it} \cdot shock_{mt-1}) + \eta_i + \phi_{st} + \epsilon_{imst} \quad (1)$$

where Y_{imst} is a measure of net migration for household i from municipality m in state s in year t. *exposed* is an indicator that the household has at least one member living in the U.S. at the beginning of year t. Notice that *exposed* is a lagged variable, and as such, its value in year t depends on migration up to the year $t-1$, and not on contemporaneous migration decision. By doing this, we avoid any mechanical positive

[18]The first type of households do not affect our identification since they exhibit no variation and thus should be captured by the household fixed effects. The omission of the second set of households should not affect our identification as long as the 2005 cut date is orthogonal to household migration decisions.

[19]We define as adults those members of the household who are over 15 years old, which corresponds to the age of the youngest migrants in the EMIF.

correlation between our exposure measure and the net migration index. *shock* is the municipality-year specific shock computed from municipality m's geographic distribution of migrants and unemployment changes at destination, as previously discussed. In all cases, the shocks are normalized so that they can be interpreted as the effect of a standard deviation increase in $shock_{mt-1}$. We include household fixed effects to control for underlying, time-invariant characteristics of the household. Also, state-year fixed effects allow us to capture time-varying characteristics in Mexican labor markets at the state level, while allowing us to estimate β_0. In our robustness checks, we consider more demanding specifications where we include municipality-year fixed effects.

In most of our regressions, Y is a net migration index, taking value 1 if the household experiences net out-migration in year t (it sends more migrants to the U.S. than those it receives back), 0 if net migration is neutral (largely, those years where a household neither sends nor receives any migrants), and -1 when the household experiences net return-migration (more members returning than leaving). We also consider an additional regression in which the dependent variable is the net number of migrants instead. To better understand the results from the baseline specification, we also run separate regressions for out-migration and return migration.

β_0 captures the response of non-exposed households to shocks in the U.S., and β_1 represents the differential response of exposed households relative to non-exposed ones. Our main interest is in the latter. In addition, we have particular interest in the heterogeneity of such a differential response across income levels.

The economic shocks in the U.S. directly impact the income of exposed households, while such an effect is absent for non-exposed households. An increase in the unemployment levels in the U.S. is likely to have a direct negative effect on the income of exposed households, and thus affect their supply of migrants, a channel that is missing for non-exposed households. Additionally, our model suggests that the differential effect of shocks in the U.S. on exposed households relative to non-exposed ones should vary with the household income level. In terms of our estimation equation, it implies that β_1 should be positive for the lowest domestic income group and decreasing in domestic income. To test these predictions, we run our baseline specification regressions by domestic labor income levels, namely, subdividing the sample by income quintiles, where the quintiles are defined at the state level.

Returning to the response of non-exposed households to shocks in the U.S., a channel through which these households may be affected is information sharing. Imagine a household without migrants that lives in Mexican municipality m, which has migrants in American city y. Due to the presence of these migrants, if a member of the household is considering where to migrate in the U.S., it is likely that she goes to y. Thus, if y

receives a negative shock, this shock could have an impact on the household's decision to send someone to the U.S. by reducing its expectations about earnings abroad. Thus, we would expect β_0 to be negative.

However, such an effect hinges on households obtaining information about shocks in the U.S. mainly from individuals in their community. While there is some evidence suggesting that individuals rely on social networks to acquire information about labor market opportunities abroad (McKenzie, Gibson, and Stillman 2013; Munshi 2003), recent evidence suggests that other channels are also important (Farré and Fasani 2013).[20] Thus, if other non network-specific sources provide relevant information for migration decisions, it is less likely that our measure of shocks explains migration decisions of non-exposed households.

Additionally, recent literature shows that labor demand conditions in the U.S. have effects on both Mexican migrants and non-migrants. Schnabl (2007) finds that increased labor demand in the U.S. improves the earnings of non-migrants in Mexican communities, through the effect of larger remittances on the demand of domestic products. This channel would drive our estimates of β_0 towards positive values, as larger unemployment in the U.S. translates into lower income for non-exposed households in Mexico, thus increasing their incentives to migrate. Overall, we remain skeptical about the sign of the effect of the shock on non-exposed households.

Notice that the variable *shock* is municipality-year specific, but constant across income/skill levels. At first glance, this may seem problematic. However, consider the predictions of our model: negative economic shocks at destination generate additional migration from exposed low income/skill Mexican families, while driving higher income/skill individuals back to Mexico. For heterogeneity in economic shocks to account for this pattern in migration (instead of the income channel we discuss in the theoretical framework), it would need to be the case that general unemployment changes are negatively correlated with unemployment in low-skill occupations, which is at odds with the trends observed in the recent recession. Thus, considering changes in general unemployment instead of quintile specific ones, if anything, should bias our empirical results against confirming the implications of our model. Moreover, in Section 8 we compute income quintile specific shocks and show that our main findings remain unchanged.

[20] Farré and Fasani (2013) show that media exposure affects internal migration decisions of Indonesian individuals.

6 Results

We begin by describing some features of our data in terms of observed migration for Mexican households by income quintiles. Panel A of Table 5 shows that the annual average unemployment rate in the U.S. was increasing throughout the years of our sample, reaching its highest levels in 2009 and 2010. Panel B describes how the income distribution of households who experience net out-migration each year evolved during the 2006-2010 period. Households in the highest income quintile have overall lower out-migration rates. More importantly, the table shows that, as the economic conditions of the U.S. worsen, the income distribution of Mexican households that experience migration changes. The relative share of migrants coming from the two lowest income quintiles increases by over 6% between 2006 and 2010, while the share of those coming from the top 40% in the income distribution falls by almost 5%. The trends presented in Table 5 suggest that negative shocks in the U.S. labor market are associated with an increased negative selection of new migrants. This observation is in line with the implications of our model. To better understand what is driving these aggregate results we turn to the econometric specifications outlaid in section 5.

We present our main results in Panel A of Table 3. In these regressions, we estimate equation (1) where the dependent variable is the net migration index previously discussed. While exposed families are unconditionally less likely to send an extra migrant for all income levels (specification not reported), we are primarily interested in the differential response of exposed families (which are directly affected by the economic conditions in the U.S.) to the unemployment shocks. Therefore, in all regressions we focus on the comparison of the interaction term with respect to the shock, β_1, and the behavior of the interaction term across income quintiles.

The positive coefficient of the interaction term in column 1 indicates that, for low-income households, negative shocks in the U.S. are associated with higher values of the net migration index (higher levels of out-migration). This result suggests the presence of an added worker effect in the international migration context for poor Mexican families. This is one of our key findings. In terms of our theoretical framework, the U.S. shock triggers a large income effect for these exposed families, who consequently respond by increasing their number of migrants to the U.S. with the purpose of compensating for their income loss.

Also consistent with our predictions, the estimation of β_1 is decreasing as we move to the right of the income distribution. In fact, the coefficient is significantly negative for the two highest quintiles (columns 4 and 5). The rationale our model provides for this is that, as domestic income increases, the substitution effect emerging from the negative shock at destination becomes dominant. This substitution effect leads families to reallocate their labor supply in favor of the domestic market after the negative shock in the U.S. diminishes the migration premium.

In terms of magnitude, the estimated coefficients suggest that a one standard deviation increase in the destination unemployment rate leads to an increase in the net migration index equivalent to roughly 5 percent of a standard deviation for exposed households in the lowest income quintile. The effect is slightly stronger for the top quintile group but in the opposite direction.

The estimates of the level of the shock variable capture the effect of changing economic conditions of those that belong to the U.S. network of non-exposed families. These coefficients are positive in Table 3. This result may seem somewhat puzzling, as it suggests that non-exposed families are more likely to move to the U.S. when the received shock is negative. One channel through which non-exposed families could be affected by the shock is information sharing. However, as we discussed in section 5.2, the relevance of this mechanism is not clear. When acquiring information on foreign labor market conditions, non-exposed families could place more weight on information sources that are not network-specific (e.g., mass media). Moreover, a positive coefficient is in line with Schnabl (2007) findings that the earnings of non-migrant Mexicans are affected by economic conditions in the U.S. through demand via fluctuations in remittances. This is a mechanism through which unemployment shocks in the U.S. may negatively affect the earnings of non-exposed households in Mexico, who in turn become more likely to migrate as they get poorer.

Nevertheless, the estimates of β_0 are not consistently significant and the point estimates are very small. For the highest and lowest quintiles, the absolute value of β_1 is over 50 times larger than the point estimates of β_0. This difference in magnitudes reflects the fact that the migration decisions of exposed families are much more sensitive to municipality-specific US unemployment shocks than those of non-exposed families. Additionally, the estimates of β_0 are not robust to our different specifications. In particular, as we will discuss in the next section, when we restrict our sample to municipalities with better information on the geographic distribution of migrants, this coefficient becomes insignificant (see Panel B of Table C4). Finally, our estimated coefficients for β_0 can be partially capturing the fact that some families who are actually exposed appear as non-exposed in our sample.

In Panel B of Table 3, we run regressions considering as dependent variable the net number of migrants (number of household members going to the U.S. minus number of members coming back to Mexico) in the household-year observation, instead of the index previously presented. The results are consistent with those of Panel A in Table 3 and with our model's predictions. The coefficients suggest that, at the intensive margin, the response of high-income families is stronger than that of low-income families, and that the intensity of the adjustment increases with domestic labor income. In this case, the interpretation of the coefficients is more straightforward. The interaction coefficient in column 1 suggests that, conditional on already having at least one member abroad, a one standard deviation increase in foreign unemployment leads families in the lowest income quintile to increase their number of members in the U.S. by 0.007 individuals on average. In the highest quintile, a shock of the same magnitude is associated with the return of 0.016 migrants to the household at origin (approximately 8 percent of a standard deviation) .

In order to better understand what is driving our results, we separate the analysis of out-migration and return migration. In Panel C of Table 3, we focus on household out-migration. In these regressions, our dependent variable is a dummy taking the value 1 when the household experiences positive net migration to the U.S., and 0 otherwise. The results are very similar to those of Panel A of Table 3, when we use the migration index instead. Namely, exposed families in the lowest income quintile have a positive and significant coefficient for the interaction term, which translates into an increased probability of sending additional migrants after a negative shock is received. In turn, the coefficient is negative and significant in columns 4 and 5, implying that the same shock decreases the probability of high-income families increasing their labor supply in the U.S.

In Table 3, Panel D we focus on return decisions. In this case, the dependent variable is a dummy taking the value 1 when a household experiences negative net migration (members come back). The results show that the returning decisions for high domestic income households are more sensitive to negative shocks in the U.S. than for low domestic income households. The point estimates are increasing in domestic income and they become significant for households in the two highest quintiles. These results are consistent with the prediction that a negative shock in the U.S. translates into a negative migration premium for the high domestic earners.

Summarizing, our results are accounted for by the fact that deteriorating labor market conditions in the U.S. lead to heterogeneous responses across domestic income quintiles in two dimensions: i) the probability of sending additional migrants, and ii) the probability that migrants return.

7 Robustness Checks

We perform a series of robustness checks that we divide in two groups for ease of exposition. First, we present some alternative specifications to address potential endogeneity and measurement error issues. Later, we introduce additional results that alleviate concerns stemming from the nature of the migration data provided by the 2010 Mexican Census.

7.1 Endogeneity and Measurement Error

We first address the fact that, since income is measured in 2010, this measure might be affected by contemporaneous migration decisions of the household. To discard this concern we consider income quantiles not by reported income but by *predicted* income, where the fitted values are obtained from pre-determined variables: linear and quadratic household head age, linear and quadratic education of the household head (in years), as well as household assets. Alternatively, we abstract from income measures altogether and run separate regressions by household education quintiles. For each household, we compute the average years of education of the household adult members.[21] We consider this measure of household education level to be the closest to our theoretical framework, where families are characterized by a single skill level.

Table C3 shows the results of these two alternative specifications. Our main findings are confirmed. When we split the sample by education quintiles (Panel B), the only difference with respect to our baseline regression comes from the coefficient on the most educated households (column 5). In this case, the point estimate is smaller in absolute terms than that of the third and fourth quintiles, and it is not statistically significant.However, this is not striking since most educated households have lower migration rates than the rest of the sample, which makes harder to find an effect for this group. Indeed, out of all the household-year observations with positive net migration in our sample, fewer than 10% belong to households in the highest education quintile.

Another concern with our empirical strategy is related to the measurement of the municipality-specific geographical distribution of migrants. This is the basic input to compute the shock received by *exposed* households and, for some municipalities, it relies on a relatively small number of interviews in the EMIF survey, making our measurement very noisy. To address this issue, we restrict the sample to those Mexican municipalities

[21] Those who are at least 25 at the time of the 2010 Mexican Census.

for which we observe at least 10 migrants in the EMIF. The cost of this strategy is that it produces a sample of larger, more urban and richer municipalities.[22,23]

Recent papers (Bohn and Pugatch 2013; Feigenberg 2013) show that changes in border enforcement have an important effect on migration rates from Mexico to the U.S. This might be concerning for our strategy, especially if the allocation of border patrol resources along the frontier is correlated with local labor market conditions in the U.S. To address this issue, we have identified the most common crossing city (out of the 7 included in EMIF) for migrants coming from each Mexican municipality and include common crossing city-year fixed effects to our baseline regressions. This way, we are able to control for changes in the intensity of border enforcement that might affect migrants from different municipalities differently.

We also consider the role played by recent migration rates in the household's origin municipality. If recent past migration is correlated with both the current probability of migrating and economic shocks at destination, it could bias our estimates of interest. To control for this, we include as additional regressors the shares of households from each income quintile in municipality m that experienced net positive migration in $t-1$. We then run

$$Y_{imst} = \delta \cdot exposed_{it} + \beta_0 \cdot shock_{mt-1} + \beta_1 \cdot (exposed_{it} * shock_{mt-1}) + \sum_{q=1}^{5} \gamma_q \cdot propY_{qmt-1} + \eta_i + \phi_{st} + \epsilon_{imst}. \tag{2}$$

where q represents income quintiles. These account for the fact that the composition of previous migratory waves may be relevant for both the unemployment rate at destination and the propensity to migrate.

Finally, we may worry that unemployment shocks in the U.S. might be correlated with other shocks that then confound our estimates. For that to be a true concern, these shocks would also have to propagate through income quintiles as unemployment shocks do. Even though such case is unlikely, we conduct a specification including municipality-year instead of state-year fixed effects. We then run[24]

$$Y_{imst} = \delta * exposed_{it} + \beta_1 * (exposed_{it} * shock_{mt-1}) + \eta_i + \phi_{mt} + \epsilon_{imst}. \tag{3}$$

[22]The number of observed migrants per municipality in the EMIF is an increasing function of the size of such municipality.

[23]This is of particular importance since we define income quintiles at the state level, and thus, a relatively large fraction of low-income households comes from poor municipalities within each state.

[24]For this exercise, we restrict our sample to the subset of municipalities with 10 or more observed migrants in the EMIF.

where note that β_0 disappears as it is subsumed by the municipality-year shock.

The results of this group of exercises are presented in table C4. In Panel A, we only use the observations from the subset of Mexican municipalities with more information on previous migrants. Panel B includes common crossing city-year fixed effects. In Panel C we control for recent migration flows, and in Panel D we include municipality-year shocks.

All specifications render similar results. In all cases, there is clear heterogeneity in the response of households to shocks across income levels. More specifically, the interaction term is decreasing in all cases, and the point estimate remains positive and significant for the lowest-income group. We also observe that in most of these alternative specifications, the absolute value of our estimates for β_1 is slightly larger than in our baseline regressions, especially when we restrict the sample to municipalities with more migrants in the EMIF (Panel B).

7.2 Mexican-born Unemployment

For our baseline analysis we construct labor market shocks in the U.S. using information on unemployment rates of the overall population in the U.S. While we could have instead restricted to the employment situation of the Mexican-born population in the U.S., such a restriction delivers a significantly smaller sample size and thus hurts the precision of the measurement of the shocks. Indeed, the cross-sectional standard deviation of the shock when measured using only Mexican-born individuals increases by a factor of around ten with respect to our baseline shock.[25] Moreover, the unemployment situation of the non-Mexican-born population should be informative about the situation of the Mexican-born ones. However, foreign-born workers present greater geographical mobility than natives (Cadena and Kovak 2013). Thus, using unemployment measures of the overall population in the U.S. may bias our estimates because of rapid relocation decisions. To address this concern, we recompute unemployment shocks restricting to the CPS sample of Mexican-born population and re-estimate our baseline regressions. Notice that again we assume that the shocks are homogeneous across income levels.

As Table 6 shows, our main findings are robust to this alternative way of computing the unemployment shocks. Namely, lower-income households increase their migration rates when their members face negative economic shocks in the U.S. The main differ-

[25]In principle, the Mexican-born unemployment rate could be subject to less measurement error since it captures the labor market shocks specific to our population of interest. However, the significant sample size restriction probably outweighs such benefit.

ence in this set of results is the smaller (in absolute terms) and insignificant coefficients for higher income group. We attribute this to the fact that the information contained in the CPS is more representative for lower-income Mexicans than higher-income ones. Throughout the CPS waves we use, most observations of Mexican-born individuals correspond to individuals working in industries typical of lower-income workers. For example, over 55% of them concentrate in agricultural production, construction, eating/drinking places, grocery stores, hotels, landscape/horticultural services, meat products, private households, services to dwellings, and trucking services.

7.3 Migration Data

Our migration data, coming from the Mexican Census, presents two main shortcomings. First, by reporting exclusively the last trip of each migrant, it prevents us from identifying repeated trips of individuals who migrate to the U.S. repeatedly during our period of analysis. In our empirical analysis we have no choice but to neglect this problem, which generates measurement error in both our outcome variables and potentially the exposed household variable. The way in which this might bias our results, if at all, is not evident. However, as an additional exercise, we run our baseline regression on the subset of municipalities that present lower levels of repeated migration. To identify these, we use information from the 2006-2010 waves of the EMIF survey on the municipal share of migrants to the U.S. that report that they have previously migrated within 5 years.[26] We then exclude from the regression those municipalities above the median of such municipal share.

A second concern stemming from the Census data on migration is that data on the year of return of those individuals who migrated to the U.S. before June 2005 and returned to Mexico between 2005 and 2010 is missing. In our previous specifications, we exclude those households who have migrants in that situation. To address how such sample restriction affects our results, we estimate our baseline equation including those households. To do this, we estimate the missing year of return of the *pre-2005 migrants* using household observable characteristics. In a first step, we use the households with migrants between 2005 to 2007 and estimate a multinomial logit of length of stay (in years) on a set of household observable characteristics. We then use these estimates to predict the length of stay of the *pre-2005 migrants.* The underlying assumption in this exercise is that two migrants coming from the same Mexican state and observably resembling households have US migration spells of similar duration, regardless of when they left, and therefore, of the shocks they faced. While such an assumption might

[26]7.1 % of migrants meet this criterion in the median municipality

introduce some noise, we obtain extra information from additional migration decisions of other members in those previously excluded households.

Table C5 presents the results of these additional exercises. Panel A restricts the sample to municipalities with lower shares of repeated migrants, and Panel B imputes the date of return for the pre-2005 migrants. The results remain very similar to those of our baseline estimations. In Panel B, when we impute the return date of pre-2005 migrants, the difference in the response across income quintiles becomes more stark, with the three highest quintiles showing a significant negative term for the interaction.

8 Alternative Mechanisms

In this section, we discuss the implications of relaxing our framework in two different dimensions. We consider the possibility of introducing heterogeneity across income quintiles in i) the unemployment shocks received by households, and ii) moving costs.

8.1 Heterogeneous Unemployment Shocks

In our baseline analysis we assume that the municipality-year specific unemployment changes are common to all income groups. However, there is the possibility that labor market shocks are heterogeneous across households with different income. This introduces the concern that our results may arise from variation in how our common unemployment measure correlates with the actual shock received by migrants from different income groups. We perform two exercises that rule out such a concern.

To construct income specific shocks, we first exploit that the presence of Mexican migrants in different industries in the U.S. varies across the wage distribution. To determine the Mexican income quintile to which each migrant worker in the U.S. belongs to, we assume that Mexican migrants in quintile q of the Mexican born income distribution in the U.S. come from households in the same quintile q of the income distribution in Mexico.

We use data from the American Community Survey (ACS) for the years 2005 to 2010. We first divide the Mexican born workers by quintiles of the Mexican born income distribution in the U.S. For each quintile, we compute the industry distribution for each year-destination cell (at the 2-digit NAICS classification level). We then compute the unemployment rate specific to each quintile-year-destination using industry-specific unemployment rates at destination from the Current Population Survey (CPS) December wave of each year.[27] We then follow the same strategy described in section 5.1 to compute the unemployment shocks received by Mexican municipalities, only that now, instead of having one municipality-year specific shock, we have five municipality-year-quintile shocks.

The outcome of this exercise, presented in Table 4 by income quintiles, is reassuring. Constructing quintile-specific shocks leaves the signs and patterns of our coefficients largely unaffected. This gives us confidence that our original results are not driven by heterogeneity in the unemployment changes across income quintiles.[28]

We then conduct a second exercise where we instead consider quintile-specific origin-destination matrices. These allow us to construct municipality-quintile specific unemployment changes at destination. For this purpose, we exploit the fact that EMIF respondents also report their education level. Using information from the Census, we compute the average income of a household from a Mexican municipality m, with years of education x.[29] We then impute to each observation in the EMIF its expected income, and divide by quintiles. This way, for a given municipality of origin, we potentially have five origin-destination matrices, one for each income quintile.[30] We finally compute the municipality-quintile specific shocks following the previously described strategy.

This exercise includes variation in unemployment shocks at destination arising from differences in the geographic distribution of migrants from different income levels within each origin municipality. The results presented in Table 5 show again the main features we observe in our baseline specification. They then provide additional evidence that our baseline empirical estimates are not the product of heterogeneity in the unemployment shocks across households with different income.

[27]The larger sample size of the ACS data allows us to estimate the industry compositions more accurately than if using the data from the CPS. However, we did not use the ACS data to construct quintile-specific unemployment shocks since, being an annual survey, the ACS data only provides annual averages of unemployment. To be consistent with the construction of our baseline unemployment shock, which is obtained using changes in December unemployment rates, we then use the CPS that it is published monthly to construct our quintile-specific unemployment shocks.

[28]We also conducted the exercise by education quintiles instead of income quintiles and find qualitatively similar results.

[29]We use the household head education.

[30]Notice that some municipality-quintile cells are empty, especially in the case of municipalities with few migrants observed in EMIF. Consequently, we have less observations than in our baseline regressions.

8.2 Heterogeneous Costs of Moving

The literature has considered heterogeneous moving costs to explain the selection patterns of migrants. In principle, information acquisitions costs (Munshi 2003; McKenzie, Gibson, and Stillman 2013) together with the financial constraints (Angelucci 2013; McKenzie and Rapoport 2010) might vary across income or educational levels. In our framework, moving costs play a secondary role in explaining such patterns. Next, we argue that heterogeneity in migration costs cannot account for our results.

The literature has emphasized that moving costs are relatively low for high-income individuals, and could be prohibitively large for poor potential migrants. If we introduce such migration cost structure in a static model where individuals are the decision-making units for migration decisions instead of the household, we would obtain predictions that would be inconsistent with our empirical findings . However, if we allow for a dynamic setting, while such a model could accommodate some of our empirical findings, it would be at odds with others.

Consider a simple two-period model in which individuals make moving decisions in each period. Consider a low-income migrant that starts in the U.S. in period 1. If such an individual suffers an unemployment shock in period 1, she can either return to her country of origin or she can stay in the U.S. If she returns to her country of origin, in case she decides to migrate back to the U.S., she might have to pay a high migration cost in period 2. The migration cost might be high enough that, the migrant might decide not to return to her country of origin in period 1. Consider, in turn, a high-income migrant that faces the same scenario but instead has a low cost of migration. Then, it is more likely that the high-income migrant returns to her country of origin when facing an unemployment shock in period 1. Thus, a dynamic model of individual migration where poorer individuals face higher migration costs would deliver that richer migrants are more likely to return when facing unemployment shocks in the U.S. This prediction, in fact, is in line with our results on return migration in Panel D in Table 3.

However, our findings on out-migration in Panel C in Table 3 are impossible to reconcile with this model. A poor potential migrant would never migrate to the U.S. when there is an unemployment shock at destination. However, we observe that unemployment shocks at destination are followed by increased migration by low-income households. Therefore, a framework that abstracts from the role played by households as decision-making units for migration decisions cannot account for all our results, even when allowing for the heterogeneous migrating cost structure considered in the literature.

9 Conclusion

We exploit variation across Mexican municipalities in the geographical distribution of past migrants to the U.S. to explore the relationship between shocks at destination and migration decisions. The evidence we present suggests that the migration decisions of families with members working in the U.S. (exposed families) are affected by labor market shocks at destination in a different way than non-exposed ones. Moreover, the differential impact of the shocks on exposed families is heterogeneous across domestic income levels. Low-income Mexican families respond to negative shocks at destination by increasing their number of migrants (i.e., they send additional members to the U.S.), while higher-income families have their members return.

We interpret our results using a simple theoretical framework in which households are the migration decision-making units. The heterogeneity of the responses is a consequence of the relative magnitudes of the income and substitution effects faced by exposed families upon shocks. For exposed low-income families, a shock at destination has a sizable impact on their budget, triggering a large income effect. They compensate this income loss by sending additional members to work in the U.S. Conversely, for exposed high-income families, the substitution effect dominates and they reduce their migration rate when the migration premium decreases.

Our results contribute to explain why migratory movements to traditional destinations may persist even in the midst of economic downturns at such destinations. Negative economic shocks in the receiving country affect the income streams of sending communities, which become poorer. This triggers an income effect that may induce some subsets of the origin households to increase their migration rates. This mechanism is especially relevant in countries with historically high levels of migration such as Mexico.

This paper is informative to the literature that studies selection patterns in migratory flows. The effect of the shocks on the income of origin households has non-trivial consequences for the composition of the migrant population. Worsening labor market conditions at destination drive high-skilled migrants back home, while increasing the number of low-skilled individuals coming from already exposed families. This is a channel traditionally ignored by the literature.

Our results also have implications for issues regarding development and poverty. According to our framework, the response of exposed low-income families to shocks in the foreign labor market is driven by their dependence on foreign income to reach a minimum level of consumption. Consequently, they are forced to increase their migration rates when economic conditions abroad are worsening, creating a dynamic in which poverty reinforces itself.

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Appendix A: Data

A.1 Origin-Destination Cells

The EMIF Norte is designed to measure‘ the migration flows from and to Mexico across its northern border with the U.S. To do this, the sampling design (whose final goal is to draw conclusions about the total flow of migrants) consists in defining time-place slots at the Mexican border cities to conduct interviews on individuals who are likely to be migrants. The sampling points within cities are bus terminals, airports, international crossing bridges, and Mexican custom points. The survey is able to capture both legal and illegal immigrants.

The information on destination in this database is tallied at the state level, but for those states with high historical levels of Mexican migration, it is disaggregated at the city level. For example, the state of Montana as a whole is a destination, but in Arizona, Tucson, Nogales, Phoenix, Green Valley, Casa Grande, and all other cities (as a single category) are coded as separate categories. In total, we have 81 destinations. Out of all the potential origin-destination cells we have, there is at least one observation in 4,857 of them and, on average, we observe 2.19 migrants in these.

A.2: Migration Variables

Sample Restrictions: The Census provides information on migratory movements from the year 2005 to 2010. We observe three types of individuals:

1. Individuals who were living in Mexico in June 2005, and did not move to the U.S. during the time period considered.

2. Individuals who were living in Mexico in June 2005, and moved to the U.S. at some point of the period considered, irrespective of whether they returned to Mexico or not. This is our definition of *migrant*. For each of these individuals, information on the month and year of their trip to the U.S. is reported, as well as month and year of the returning trip if the individual returned.

3. Individuals who were living abroad in June 2005 and had returned to the household by the moment of the Census. We call these *pre-2005 migrants*. For these individuals, no information on the date of the returning trip is provided.

In households with at least one *pre-2005 migrant*, the values of the dependent migration variables and the exposed dummy are unknown, since we have no information on the date of the returning trip. Therefore, in our baseline, we restrict our sample to households with no *pre-period migrants*. In doing this, we drop around 3% of our sample. Additionally, individuals who were living abroad by June 2005 and had not returned to the household by the moment of the Census are not captured. In section 7.3, we conduct a robustness check to address the effect of such restrictions.

Additional issues: As in most data sets used for studies on migration, we lack information on those households who moved entirely to the U.S. during this period. However, as long as all members move together in a single trip, this does not pose a serious problem for the estimation of our main effect of interest, which has to do with the adjustments made by those households whose members are partially abroad (those who are in an interior solution according to our theoretical framework). It is also a problem of a lesser magnitude than for those studies exploiting data for other periods of time given that that, as we mentioned earlier, total migration during the years we consider is significantly lower than in previous years.

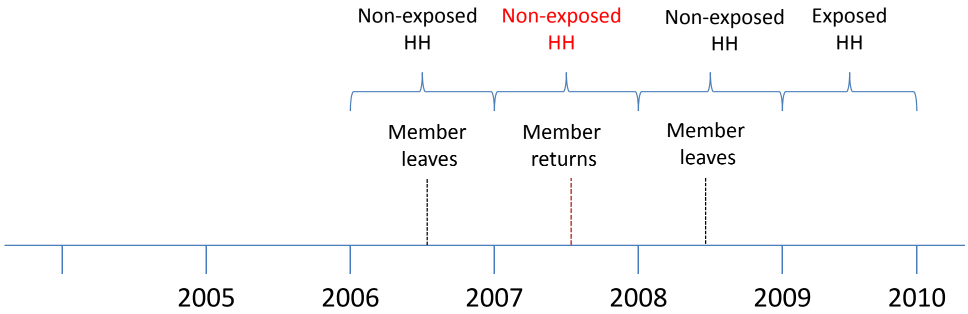

Figure A1: Individual with multiple trips
Example case: A migrant leaves for the U.S. during 2006, returns to Mexico in 2007 and goes back to the U.S. in 2008, where she remains until the end of the period. The Census provides no information on the first trip. Consequently, in our baseline regressions we are misscoding the household as *non-exposed* in 2007.

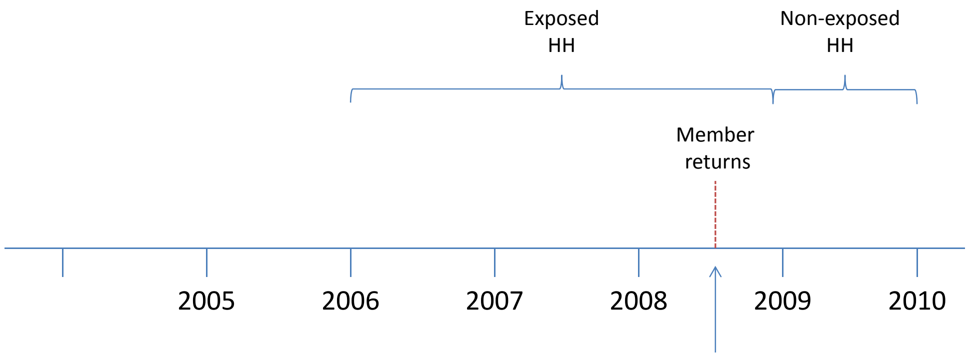

Figure A2: Pre-2005 migrants
Example case: A migrant leaves for the U.S. before 2005 and returns to Mexico during 2008. In this case, the Census provides no information on the date of return. Therefore, we have no information on the actual years the household was exposed. We drop these households in our baseline estimations.

Appendix B: Figures and Tables

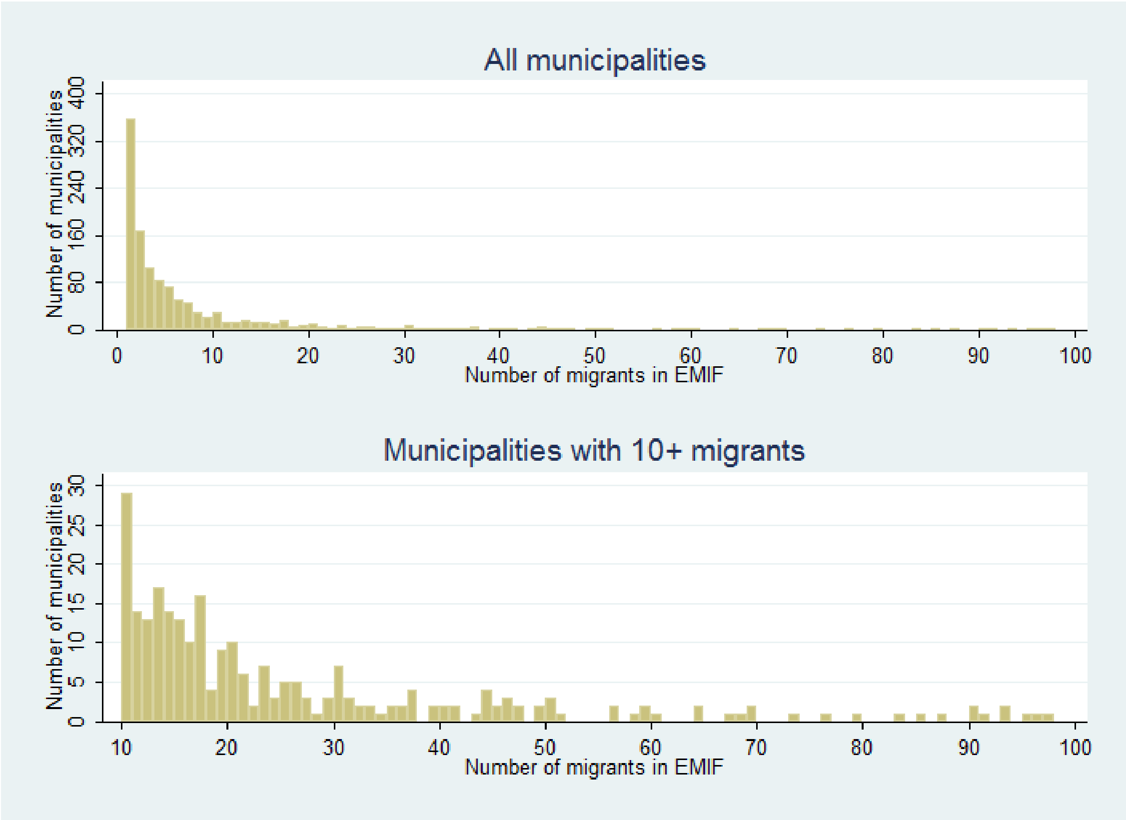

Figure 1: Distribution of Municipalities by Number of Observed Migrants in EMIF

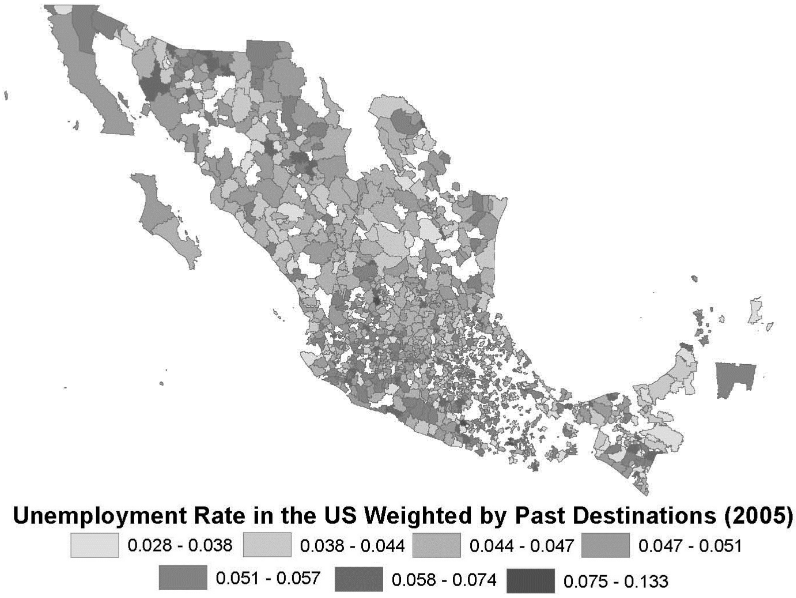

Figure 2: Unemployment Levels in 2005

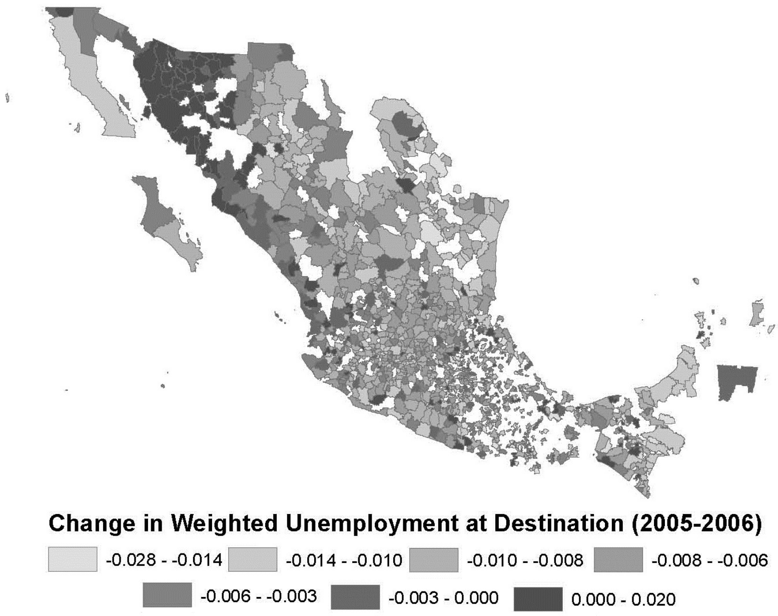

Figure 3: Change in Unemployment 2005-2006

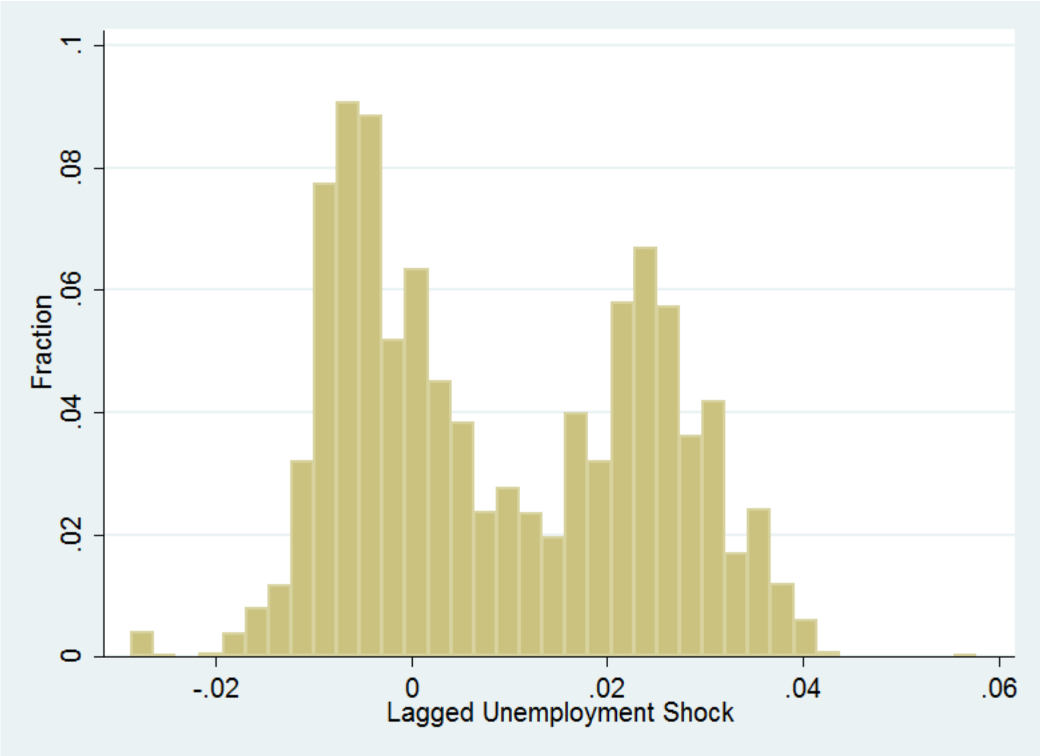

Figure 4: Distribution of Unemployment Shocks

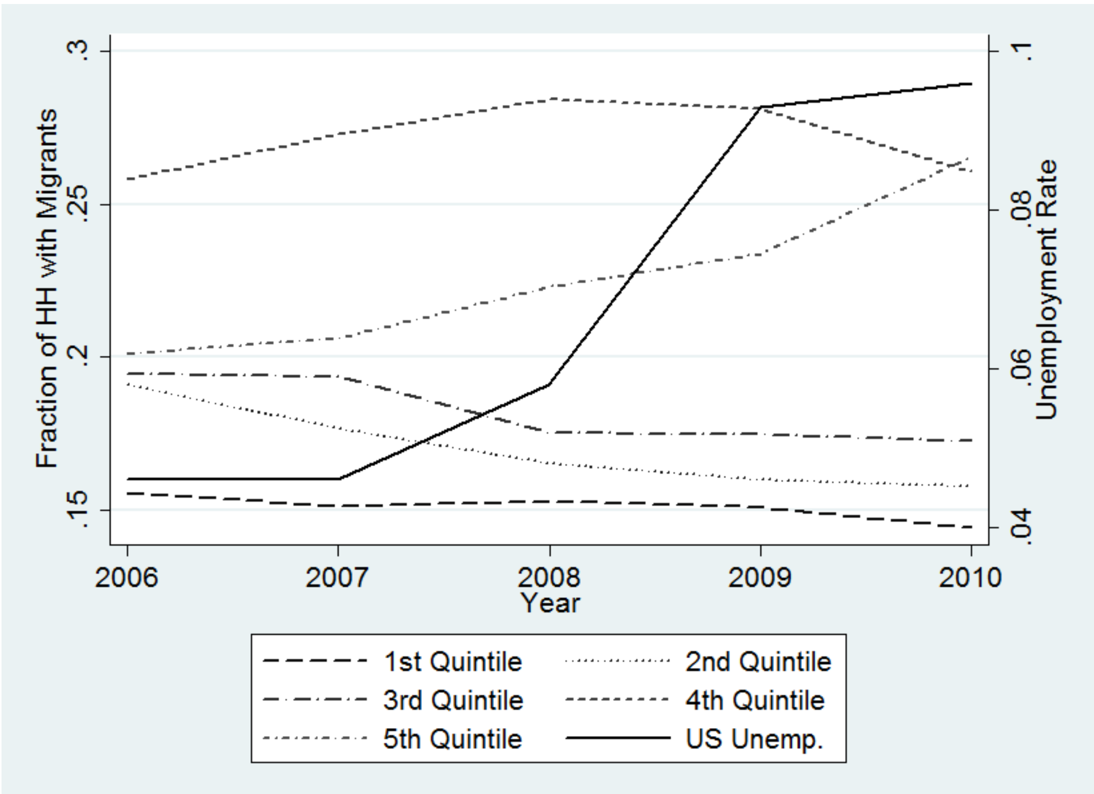

Figure 5: US Unemployment and Migration Rates by Income Quintile

Table 1: Summary Statistics by Income Quintiles

	Income Quintile					
Variable	5	4	3	2	1	Total
			Panel A. All Households			
Number of Households	187,050	298,314	262,718	266,309	265,151	1,279,452
Domestic Labor Income (pesos/month)	1,150.37	2,441.12	4,831.82	7,950.12	21,023.97	7,740.67
	(1,147.58)	(1,781.369)	(1,948.94)	(2,953.11)	(26,711.94)	(14,233.55)
Predicted Labor Income (pesos/month)	5,412.14	5,293.26	6,970.80	8,751.60	13,068.81	7,979.48
	(5,481.87)	(5,580.41)	(5,821.76)	(6,041.40)	(6,854.07)	(6,652.70)
HH Head Education (years)	5.2	5.6	6.9	7.8	10.4	7.3
	(4.0)	(4.0)	(4.3)	(4.7)	(5.4)	(4.9)
HH Head Age	50.2	45.4	44.1	45.0	46.8	46.1
	(16.7)	(15.9)	(14.8)	(13.9)	(12.7)	(14.9)
			Panel B. Households Changing Exposure Status			
Number of Households	6,599	8,421	5,936	5,633	4,969	31,558
	(3.53%)	(2.82%)	(2.26%)	(2.12%)	(1.87%)	(2.47%)
Domestic Labor Income (pesos/month)	737.89	1,918.89	4,362.07	7,354.59	18,410.56	5,698.46
	(920.62)	(1,618.06)	(1,714.83)	(2,440.49)	(18,794.59)	(9,660.76)
Predicted Labor Income (pesos/month)	5,651.74	5,334.22	6,549.46	7,878.86	10,784.48	6,940.07
	(4,267.71)	(4,690.82)	(4,537.76)	(4,678.63)	(5,934.13)	(5,152.01)
HH Head Education (years)	4.2	4.9	5.4	6.1	7.6	5.4
	(3.5)	(3.6)	(3.8)	(4.2)	(5.2)	(4.2)
HH Head Age	51.2	48.4	47.3	47.6	49.4	48.8
	(14.1)	(13.8)	(13.7)	(12.4)	(11.8)	(13.3)

Note: For these statistics, the unit on observation is the household. The values of the variables are those reported in the 2010 Mexican Census. The identity of the household head is self-reported.

Table 2: Observable characteristics of census sample of adults from households with migrant and EMIF migrants

	Census sample of adults from households with migrants	*EMIF migrants*
Education years	6.83	7.58
	(3.34)	(3.74)
Age	37.43	33.22
	(8.93)	(12.37)
Income (Mexican pesos/month)	3,396.36	3,082.02
	(5,754.6)	(6,176.3)
HH members	5.67	5.25
	(2.21)	(2.70)

Note: We define census adults from households with migrants those individuals who are over 15 years old. Labor income in the EMIF is reported as income earned in different time units (weekly, daily, semi-monthly or monthly), which we transform to monthly values. Number of members in households in the Census is equal to the number of individuals residing in the household at the time of the interview plus post-2005 migrants that remain in the US.

Table 3: Effect of shocks on migration outcomes

Income quintile	5	4	3	2	1
			Panel A. Net Migration Index		
shock	0.0001	0.001**	0.0007**	0.0003	0.0002
	(0.0004)	(0.0005)	(0.0002)	(0.0002)	(0.0003)
exposed*shock	0.009***	0.002	-0.004	-0.007**	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R-squared	0.252	0.260	0.295	0.302	0.296
			Panel B. Net Number of Migrants		
shock	0.0002	0.001**	0.008**	0.0002	0.0001
	(0.0005)	(0.0006)	(0.0003)	(0.0003)	(0.0003)
exposed*shock	0.007**	-0.003	-0.008**	-0.008***	-0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
R-squared	0.216	0.223	0.252	0.260	0.250
			Panel C. Out Migration		
shock	0.00009	0.001**	0.0005**	0.0003	0.00009
	(0.0004)	(0.0005)	(0.0002)	(0.0002)	(0.0002)
exposed*shock	0.009***	0.002	-0.002	-0.003*	-0.004**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.192	0.194	0.206	0.207	0.198
			Panel D. Return Migration		
exposed	0.118***	0.126***	0.166***	0.175***	0.179***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
exposed*shock	0.00007	0.00002	0.001	0.003*	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.091	0.096	0.129	0.138	0.143
Households	187,050	298,314	262,718	266,309	265,151

Note: In all specifications the unit of observations is the household-year. We include household and state-year fixed effects and we cluster standard errors at the municipality level. We control for a dummy indicating whether the household has migrants abroad (variable *exposed*). *shock* is the Mexican municipality specific change in US unemployment in previous year. Income quintiles are defined at the state level using reported income. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effect of shocks on different outcomes. Heterogeneous industry composition

Income quintile	5	4	3	2	1
			Panel A. Net Migration Index		
shock	-0.0001	-0.00001	0.00003	0.00009	0.0001*
	(0.0001)	(0.0001)	(0.00008)	(0.00008)	(0.00009)
exposed*shock	0.007***	0.0004	-0.006**	-0.004*	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.252	0.260	0.295	0.302	0.296
			Panel B. Net Number of Migrants		
shock	-0.0002	0.00002	0.00004	0.0001	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
exposed*shock	0.006*	-0.001	-0.009***	-0.006*	-0.017***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
R-squared	0.216	0.223	0.252	0.260	0.250
			Panel C. Out Migration		
shock	-0.0001	-0.00005	-0.00002	0.00008	0.00003
	(0.0001)	(0.0001)	(0.00007)	(0.00007)	(0.00008)
exposed*shock	0.007***	0.001	-0.001	0.0003	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.192	0.194	0.206	0.207	0.198
			Panel D. Return Migration		
exposed	0.118***	0.126***	0.164***	0.176***	0.182***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
exposed*shock	0.0004	0.001	0.005**	0.005**	0.007***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
R-squared	0.091	0.096	0.130	0.138	0.143
Households	187,050	298,314	262,718	266,309	265,151

Note: In all specifications the unit of observations is the household-year. We include household and municipality-year fixed effects and we cluster standard errors at the municipality level. We control for a dummy indicating whether the household has migrants abroad (variable *exposed*). *shock* is the Mexican municipality-quintile specific change in US unemployment in previous year, taking into account heterogeneity in the industry composition of Mexican workers across income levels. Industry composition of workers is obtained from the ACS. Income quintiles are defined at the state level using reported income. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effect of shocks on different outcomes. Heterogeneous geographical distribution

Income quintile	5	4	3	2	1
			Panel A. Net Migration Index		
shock	-0.00008	0.001**	-0.000008	-0.000001	0.0003
	(0.0004)	(0.0007)	(0.0003)	(0.003)	(0.0003)
exposed*shock	0.008***	0.002	-0.005	-0.009**	-0.017***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
R-squared	0.249	0.257	0.303	0.314	0.309
			Panel D. Net Number of Migrants		
shock	-0.00008	0.001**	-0.0002	-0.00004	0.0002
	(0.0005)	(0.0008)	(0.0003)	(0.0004)	(0.0004)
exposed*shock	0.006*	-0.001	-0.010**	-0.010**	-0.021***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
R-squared	0.215	0.221	0.261	0.265	0.259
			Panel B. Out Migration		
shock	-0.00006	0.001**	-0.00005	0.0001	0.00002
	(0.0004)	(0.0006)	(0.0002)	(0.0002)	(0.0002)
exposed*shock	0.010***	0.001	-0.002	-0.005**	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.187	0.189	0.203	0.210	0.195
			Panel C. Return Migration		
exposed	0.118***	0.135***	0.184***	0.189***	0.208***
	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)
exposed*shock	0.001	-0.001	0.003	0.004	0.005
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
R-squared	0.093	0.101	0.146	0.150	0.163
Households	136,777	163,688	147,419	143,788	158,871

Note: In all specifications the unit of observations is the household-year. We include household and municipality-year fixed effects and we cluster standard errors at the municipality level. We control for a dummy indicating whether the household has migrants abroad (variable *exposed*). *shock* is the Mexican municipality-quintile specific change in US unemployment in previous year, taking into account heterogeneity in the geographical distribution of Mexican migrants across (imputed) income quintiles. Income quintiles are defined at the state level using reported income. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effect of shocks on different outcomes. Mexican-born shocks

Income quintile	5	4	3	2	1
			Panel A. Net Migration Index		
shock	-0.00005	-0.00001	0.00004	0.00005	0.0001
	(0.0001)	(0.00008)	(0.00006)	(0.00006)	(0.00006)
exposed*shock	0.006***	0.004**	-0.0002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.252	0.260	0.295	0.302	0.296
			Panel D. Net Number of Migrants		
shock	-0.00005	0.00001	0.00002	0.0001	0.0001
	(0.0001)	(0.0001)	(0.00007)	(0.00007)	(0.00008)
exposed*shock	0.005*	0.003	-0.0008	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
R-squared	0.216	0.223	0.252	0.260	0.249
			Panel B. Out Migration		
shock	-0.00007	-0.00001	0.0000009	0.00003	0.00004
	(0.0001)	(0.00007)	(0.00005)	(0.00005)	(0.00006)
exposed*shock	0.006***	0.002*	-0.0009	-0.000001	-0.0008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.192	0.194	0.206	0.207	0.198
			Panel C. Return Migration		
exposed	0.118***	0.127***	0.169***	0.179***	0.187***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
exposed*shock	-0.0001	-0.001	-0.0007	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
R-squared	0.091	0.096	0.129	0.138	0.143
Households	187,050	298,314	262,718	266,309	265,151

Note: In all specifications the unit of observations is the household-year. We include household and municipality-year fixed effects and we cluster standard errors at the municipality level. We control for a dummy indicating whether the household has migrants abroad (variable *exposed*). *shock* is the Mexican municipality specific change in US unemployment in previous year, constructed from the Mexican-born unemployment rate at destination cities. Income quintiles are defined at the state level using reported income. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C: Additional Tables and Results

Table C1: Number of Mexican-Born Residing in US by Census Years

		Mexican Born		
Year	Foreign Born	Number	Share of Foreigners	Rank$^{(1)}$
1940	11,494,085	357,776	3.1	n/a
1950	11,454,892	451,447	3.9	n/a
1960	9,738,091	575,902	5.9	7
1970	9,619,302	759,711	7.9	4
1980	14,079,906	2,199,221	15.6	1
1990	19,797,316	4,298,014	21.7	1
2000	31,107,889	9,177,487	29.5	1
2010	39,955,673	11,711,103	29.3	1

Note: (1) Rank refers to the position of the Mexican-born relative to other immigrant groups in terms of size of the population residing in the United States in a given census year (information available since 1960). Source: Migration Policy Institute (MPI) DataHub. Data for 1940 and 1950 are from MPI analysis of decennial census data made available by Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Shroweder, and Matthew Sobek, Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota, 2010. Data for 2000 are from MPI analysis of decennial census data; data for 2010 are from MPI analysis of data from the U.S. Census Bureau's 2010 American Community Survey.

Table C2: Geographic Distribution of Mexicans in the U.S. by Metropolitan Area

Metropolitan Area	Estimate (thousands)[1]	%[1]	Mexican Born/Pop.[2]
Los Angeles-Long Beach-Santa Ana, CA Metro Area	1,768.3	15.1	14.9
Chicago-Joliet-Naperville, IL-IN-WI Metro Area	683.3	5.8	7.2
Houston-Sugar Land-Baytown, TX Metro Area	600.7	5.1	10.4
Dallas-Fort Worth-Arlington, TX Metro Area	588.9	5.0	10.3
Riverside-San Bernardino-Ontario, CA Metro Area	572.3	4.9	13.5
Phoenix-Mesa-Glendale, AZ Metro Area	346.8	3.0	11.4
San Diego-Carlsbad-San Marcos, CA Metro Area	343.9	2.9	11.4
New York-Northern New Jersey-Long Island, NY-NJ-PA Metro Area	327.9	2.8	1.3
San Francisco-Oakland-Fremont, CA Metro Area	257.1	2.2	6.1
McAllen-Edinburg-Mission, TX Metro Area	212	1.8	8.8*

Source: (1) Data on the number of Mexican Born from US Census Bureau, 2010 American Community Survey. (2) Data on the number of Mexican born individuals as a share of total population as of 2005 from the U.S. Census Bureau, 2005 American Community Survey. *The value of the variable for this Metro Area is estimated using the proportion of foreign born as a share of the population in the MA times the national average of Mexican born as a share of the foreign born.

Table C3: Effect of shocks on net migration index

Quintile	5	4	3	2	1
	Panel A. Predicted income quintiles				
shock	-0.0002	0.0003	0.001***	0.001***	0.0005*
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
exposed*shock	0.008***	0.002	-0.0006	-0.006**	-0.007**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Households	256,412	253,846	251,812	251,427	256,047
R-squared	0.285	0.280	0.269	0.272	0.291
	Panel B. Education quintiles				
shock	0.0008	0.0006	0.0008***	0.0003	0.0003*
	(0.0008)	(0.0004)	(0.0002)	(0.0002)	(0.0002)
exposed*shock	0.006***	-0.001	-0.006**	-0.013***	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Households	170,205	251,872	278,621	299,935	276,172
R-squared	0.242	0.268	0.289	0.306	0.308

Note: In all specifications the unit of observations is the household-year. We include household and state-year fixed effects and we cluster standard errors at the municipality level. We control for a dummy indicating whether the household has migrants abroad (variable *exposed*). *shock* is the Mexican municipality specific change in US unemployment in previous year. In Panel A, income quintiles are defined at the state level using predicted income from household head age (and square), household head education level (and square), and household assets. In Panel B, education quintiles are defined at the national level using years of schooling of household adults. *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Effect of shocks on net migration index

Income quintile	5	4	3	2	1
Panel A. Municipalities with 10+ migrants in EMIF					
shock	-0.001	0.0007	0.0007	0.0003	0.0005
	(0.001)	(0.001)	(0.0008)	(0.0009)	(0.0009)
exposed*shock	0.014***	0.0008	-0.003	-0.008*	-0.011**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
Households	58,894	97,907	104,141	116,537	131,432
R-squared	0.246	0.275	0.304	0.309	0.305
Panel B. Crossing point-year effects					
shock	0.0003	0.0012**	0.0008***	0.0004	0.0003
	(0.0004)	(0.0005)	(0.0002)	(0.0002)	(0.0003)
exposed*shock	0.009***	0.0008	-0.004	-0.007**	-0.012***
	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)
Households	187,050	298,314	262,718	266,309	265,151
R-squared	0.252	0.260	0.295	0.302	0.296
Panel C. Controling for recent migration in municipality					
shock	0.0001	0.0009*	0.0006**	0.0002	0.0001
	(0.0004)	(0.0005)	(0.0002)	(0.0002)	(0.0003)
exposed*shock	0.010***	0.003	-0.004	-0.006**	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Households	187,050	298,314	262,718	266,309	265,151
R-squared	0.253	0.260	0.295	0.303	0.296
Panel D. Municipality-year shocks					
exposed*shock	0.012**	-0.0001	-0.003	-0.009**	-0.012**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Households	58,894	97,907	104,141	116,537	131,432
R-squared	0.254	0.279	0.307	0.312	0.309

Note: In all specifications the unit of observations is the household-year. We include household and state-year fixed effects and we cluster standard errors at the municipality level. We control for a dummy indicating whether the household has migrants abroad (variable *exposed*). *shock* is the Mexican municipality specific change in US unemployment in previous year. In all Panels, income quintiles are defined at the state level using reported income. *** p<0.01, ** p<0.05, * p<0.1.

Table C5: Effect of shocks on net migration index

Income quintile	5	4	3	2	1
Panel A. Excluding municipalities with high repeated migration					
shock	0.0001	0.001	0.0004	0.0004	0.0005
	(0.0006)	(0.001)	(0.0004)	(0.0004)	(0.0005)
exposed*shock	0.009*	0.001	-0.007	-0.009	-0.015***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Households	60,108	95,423	77,502	75,464	70,191
R-squared	0.271	0.261	0.291	0.301	0.302
Panel B.Including pre-2005 Migrant Households					
shock	0.0001	0.001*	0.0009***	0.0005	0.0001
	(0.0004)	(0.0005)	(0.0003)	(0.0003)	(0.0003)
exposed*shock	0.008***	0.003	-0.014***	-0.013***	-0.016***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Households	194,314	305,187	270,187	273,181	271,321
R-squared	0.340	0.349	0.388	0.389	0.379

Note: In all specifications the unit of observations is the household-year. We include household and municipality-year fixed effects and we cluster standard errors at the municipality level. We control for a dummy indicating whether the household has migrants abroad (variable *exposed*). *shock* is the Mexican municipality specific change in US unemployment in previous year. Income quintiles are defined at the state level using reported income. *** p<0.01, ** p<0.05, * p<0.1.