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DEVELOPMENT BANK OF LATIN AMERICA

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ABSTRACT

We study how unemployment shocks in the United States affect Mexican households' migration decisions. We emphasize households at origin (as op-posed to individuals) as the decision-making units for migration decisions. We show that negative changes in US labor market conditions, which are diffused by household members at destination to those at origin, lead to heterogeneous migration responses by Mexican households that have members abroad. We argue that this heterogeneous response is driven by the relative magnitudes of income and substitution effects after a negative employment shock in the United States. While the income effect dominates the substitution effect for poor households, the opposite holds for richer households. These results also inform the literature on selection patterns in international migration, which suggests a new channel through which negative shocks in the host economy negatively affect the skill composition of subsequent migrants.

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SACRIFICÁNDOSE POR EL EQUIPO: SHOCKS EN EL MERCADO DE DESTINO Y LA OFERTA DE MIGRANTES DE LOS HOGARES

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RESUMEN

Estudiamos cómo shocks de desempleo en Estados Unidos afectan las decisiones migratorias de los hogares mexicanos. Enfatizamos el hogar en el origen (en oposición a los individuos) cómo la unidad que toma las decisiones migratorias. Mostramos que cambios negativos en las condiciones del mercado laboral en EE.UU., que son difundidos a los hogares en el origen a través de sus migrantes en el destino, conllevan respuestas migratorias heterogéneas por parte de los hogares mexicanos que tienen miembros en el exterior. Argumentamos que esta respuesta heterogénea se debe a las magnitudes relativas de los efectos ingreso y sustitución tras un shock negativo al empleo en EE.UU. Mientras el efecto ingreso domina al efecto sustitución en los hogares pobres, lo opuesto ocurres en hogares más ricos. Estos resultados son informativos para la literatura sobre patrones de selección en la migración internacional, al sugerir un nuevo canal a través del cual shocks negativos en la economía anfitriona afecta negativamente la composición de habilidades de los migrantes subsiguientes.

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

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August 9, 2017

Abstract

We study how unemployment shocks in the United States affect Mexican households' migration decisions. We emphasize households at origin (as opposed to individuals) as the decision-making units for migration decisions. We show that negative changes in US labor market conditions, which are diffused by household members at destination to those at origin, lead to heterogeneous migration responses by Mexican households that have members abroad. We argue that this heterogeneous response is driven by the relative magnitudes of income and substitution effects after a negative employment shock in the United States. While the income effect dominates the substitution effect for poor households, the opposite holds for richer households. These results also inform the literature on selection patterns in international migration, which suggests a new channel through which negative shocks in the host economy negatively affect the skill composition of subsequent migrants.

JEL-Classification: F22, J22, J61, O15
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1 Introduction

A growing interest in understanding the relationship between international migration and economic development has spurred research on the determinants of migratory movements from (and back to) low-income countries (Grogger and Hanson 2011; Mayda 2010; Clark, Hatton, and Williamson 2007; Dustmann 2003; Lessem 2013; McKenzie, Gibson, and Stillman 2013; McKenzie, Theoharides, and Yang 2014; Bryan, Chowdhury, and Mobarak 2014; Angelucci 2015). At a micro level, a relevant question is whether (and how) the situation at destination-labor markets affects the economic decisions of members of migrant households that remain at origin. Along these lines, previous research has shown that migrant earnings impact those decisions on several dimensions, including entrepreneurship, agricultural investment, and schooling investment (Antman 2013; Gibson, McKenzie, and Stillman 2011; Gibson and McKenzie 2014; McKenzie and Rapoport 2011; Yang 2008, 2011). However, the link between destination-labor market outcomes and the subsequent migration decisions of the members of migrant households that remain at origin has been largely neglected. In this paper, we turn our attention to this issue and investigate how the migration decisions of Mexican households with members in the US respond to labor market conditions in the US.

Theoretically, for households with members working abroad, a worsening of their migrants earnings should lead to both a substitution *and* an income effect. The former implies that the foreign market becomes less attractive after the change in economic conditions. Via the income effect, in turn, the households become poorer, which increases their incentives to send more members abroad (if the foreign market continues to be preferable to the domestic one). We formalize this notion in a simple model that predicts that the response to negative shocks in the foreign labor market is heterogeneous across the household-income distribution. For low-income households, the income effect dominates leading to increased migration (i.e., additional household members abroad). High-income families, in turn, have their members return. Thus, in a context of high levels of past migration, [1] in which remittances are an important component of the income of the household members who remain at origin, [2] economic shocks at destination may have a non-trivial impact on subsequent migration flows and their skill composition.

Our predictions resonate with the literature on the "added-worker effect," which studies

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

[2]According to `www.banxico.org.mx`, Mexico's income from remittances increased from \$3.6 billion to \$21.3 billion between 1995 and 2010.

how unemployment spells suffered by a household's primary worker lead to increased labor supply by its secondary workers, especially among credit-constrained families (Stephens 2002; Lundberg 1985). In the spirit of this literature, our paper assesses the existence of an "added-migrant effect" among low-income families with migrants abroad.

In our empirical exercise, we explore the relationship between US employment conditions and the migratory decisions of Mexican households between 2005 and 2010, which were elicited during the 2010 Mexican Census. Specifically, we use changes in expected unemployment in the US as our measure of labor market shocks. We construct Mexican municipality-year specific measures of expected unemployment in the US by exploiting municipal patterns of past migration across different destinations in the United States and heterogeneous changes in employment conditions in those destinations. Since our theory indicates that only Mexican households with members in the US should be subject to income effects when labor market conditions change in the US, we interact our measure of labor market shock with an indicator that a Mexican household has members working in the US; we denote these households as *exposed households*.

In line with our model's predictions, our empirical results show that exposed Mexican households respond to unemployment shocks in the United States in a heterogeneous fashion. Dividing the sample by quintiles according to their domestic labor income, we observe that higher-income households adjust to such shocks by bringing their members back to Mexico, while lower-income households send more members to the United States. Additionally, the response of non-exposed households is weak or non-existent.

We address many concerns regarding the robustness of our empirical results. The differential response of exposed households across income levels is robust to considering predicted – instead of realized domestic labor income and to splitting the sample by adults' education quintile, thus addressing the concern that our measure of domestic income (assessed in 2010) is itself affected by past migration decisions. Our results also hold when we restrict the sample to Mexican municipalities for which there is more precise information on the geographical distribution of past migrants to the United States, consequently dealing with concerns of bias due to non-classical measurement error. Further robustness checks show that our estimates change neither when we control for past migration rates of different income groups from the municipality of origin, nor when we account for varying border enforcement at various points of the frontier, which might be correlated with local US labor market conditions. We also address the concern that unemployment shocks in the United States might correlate with other unobserved municipality-specific shocks by including municipality-year fixed effects. Our results are also robust to using changes in expected unemployment for the Mexican-born – instead of both Mexican-born and native – population in the United States.[3] Finally, additional robustness checks deal with some limitations presented by the migration data that come from the 2010 Mexican Census.

In our baseline analysis, we abstract from the possibility that unemployment shocks in the United States could be heterogeneous across income levels. That is, we assume that all households from a given Mexican municipality are subject to the same US unemployment shock. Nonetheless, our results remain unchanged when we relax this assumption using two different approaches. First, we exploit variation in the industry composition of Mexican immigrants in the US labor market across income levels.[4] Second, we exploit the fact that, within a given Mexican municipality, poorer and richer individuals might migrate to different US destinations. The results using both approaches suggest that our findings are robust to accounting for heterogeneous shocks across income quintiles. Lastly, although we abstract from the fact that moving costs may vary along the income distribution (Chiquiar and Hanson (2005); Borjas (1991)), we discuss the implications that such costs may have for our analysis and show that they cannot account for our results.

As mentioned before, our results are closely linked to those found in the "added-worker effect" literature. The existence of a positive relationship between the unemployment of a household's primary worker and the labor supply of secondary workers has been empirically established in the context of domestic labor markets. Looking at data from rural Philippines, Dessing 2002 finds that subsistence needs lead to negative labor supply elasticities for secondary workers at low wage rates and positive ones at higher rates. In the case of urban Mexico, Parker and Skoufias (2004) also find significant added-worker effects, which are double in size during crisis than in prosperity periods. Moreover, there is significant evidence that household liquidity constraints are associated with greater responses in the labor supply of secondary workers (Stephens (2002); Lundberg (1985); Maloney (1987)).

There is also some evidence that, for households with migrants abroad, fluctuations in foreign labor markets affect their labor supply. Arango et al. (2015) show that unemployment rates in Spain and United States (traditional destinations of Colombian migrants) positively affect labor force participation in the regions of Colombia with higher historical migration rates. Similarly, Amuedo-Dorantes and Pozo (2012) find that higher levels of remittance inflows from the US decrease the labor supply of household members in Mexico. These results indicate that foreign labor market shocks have a significant income effect on households with migrants abroad, which leads to

[3] We discuss in depth the potential benefits and problems of both strategies later in the paper.

[4] Poor and rich Mexican immigrants work in different industries in the United States.

changes in their labor supply. Our paper contributes by showing that, at least in the Mexican context, low-income households with members abroad may adjust to negative shocks to labor conditions at destination by increasing their foreign labor supply (via increased migration rates).

Our paper underlines the importance of addressing migration as a decision that is made at the household (as opposed to the individual) level. We are hardly the first ones to acknowledge this. At least since the works by Mincer (1978) and Borjas and Bronars (1991), many have approached the causes and effects of migratory movements from a household-level perspective. To provide a clearer understanding of the relationship between the labor-market experience of migrants at destination and the subsequent migration decisions of their household members at origin, we track the migratory movements of each household member and exploit shocks to labor-market conditions at destination. This novel data and approach allow us to analyze the way in which household members at origin respond to labor market shocks at destination that are diffused to household members at origin by their migrant members.

Our findings inform the broader literature relating economic conditions and migration flows, which has traditionally focused on the difference in expected wages, as well as the monetary costs of migrating (Angelucci (2015)), as the determinants of migration patterns. In turn, we highlight the importance of the effect of labor market shocks at destination on households' income at origin, and how this effect significantly varies across skill levels. Our results indicate that past migration patterns interact with contemporary economic shocks at destination to shape both the size and composition of future migratory waves.

Our paper also has implications for the literature that analyzes the selection of migrants from Mexico to the United States (Borjas 1987, 1994; Borjas and Friedberg 2009; Chiquiar and Hanson 2005; Fernández-Huertas Moraga 2013; McKenzie and Rapoport 2010). Abstracting from the heterogeneity in moving costs, and departing from a simple model that predicts negative selection in the absence of remittances, our findings suggest that labor market shocks at destination have a non-trivial effect on the skill distribution of the migrant population. In particular, negative labor market shocks drive migrants from high-skilled households back to their home countries and increase the number of migrants from low-skilled households, which contributes to the negative selection of Mexican migrants to the United States.

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

2 Mexican Migration to the United States

2.1 Migration Flows

The movement of Mexican workers to the United States is a historical phenomenon that has affected the demographic dynamics of both countries. The first important flow of Mexican laborers to the United States began in the early 20$^{\text{th}}$ century with the curtailment of Japanese immigration and the advent of World War I. 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 US and Mexican governments, which was designed 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 US immigration policy. Although the act did not relax the rules on immigration from Latin America, it was followed by a steep increase in the number of immigrants from the region, especially from Mexico. The Braceros Program, through which many Mexican workers had entered the United States in previous decades, was eliminated. Consequently, an increasing proportion of the new immigrants were illegal.

Migration flows over the last two decades 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 United States 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 individuals residing in the United States, as Table C1 in the Appendix shows. Between 2000 and 2007, those flows came to a standstill, possibly reflecting the stricter US immigration policies after the 9/11 terrorist attacks. After the onset of the global economic crisis, the number of Mexicans leaving for the United States 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 United States more strongly than Mexico – net migration from the United States to Mexico was close to neutral or, at most, only slightly negative.

Over the years, Mexican immigrants have constructed social networks in their traditional US destinations, which play a major role in improving immigrants' labor market outcomes by substantially reducing information failures (McKenzie and Rapoport 2010; Munshi 2003). We exploit the fact that, since different Mexican communities have traditionally migrated to different US destinations, economic shocks in those destinations should diffuse differently to Mexican municipalities, and may have a differential impact on Mexicans' expectations about employment in the United States.

2.2 Geographic Location

Mexican-born individuals are spatially distributed across the entire US territory. California, Texas, Illinois, and Arizona have received 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 areas are located in California, three in Texas, one in Arizona, and the remaining two are in the Chicago area (which includes Illinois, Indiana, and Wisconsin) and the New York area (including New York, New Jersey, and Pennsylvania). Those ten areas account for almost half of the Mexican-born population residing in the United States in 2010. Other important metropolitan areas 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 area'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 the states of Arizona, California, and Texas, with the Los Angeles-Long Beach-Santa Ana Metro Area showing the highest value for this variable (14.9%). On the contrary, only 1.3% of the residents in the New York-Northern New Jersey-Long Island Metro Area were Mexican-born by 2005.

There was also great heterogeneity in economic performance across US areas during the period of our study. 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 (less than 1% increase in North Dakota, Alaska, and Nebraska, for example). This paper is among the first to exploit the fact that this feature of the US economy, together with the municipal patterns of past migration across different destinations in the United States, translates into considerable variation in the US unemployment shocks that diffuse to Mexican households with migrants.

3 Theoretical Framework

We develop a simple theoretical model of household migration decisions to understand how origin households with members abroad reoptimize their migration decisions when these members face an unemployment shock at destination. Our aim is not to provide a theoretical contribution, but simply to guide our empirical exercise. Following the framework by Roy (1951) 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 the wage in country i, μ_i is the baseline wage for uneducated workers in country i, and δ_i represents the returns to schooling. The literature stresses the fact that minimum wages are higher in the United States and returns to schooling are greater in Mexico, which in our framework translates as $\mu_{mex} < \mu_{us}$ and $\delta_{mex} > \delta_{us}$ (McKenzie and Rapoport 2010). Defining $\mu_{mig} = \mu_{us} - \mu_{mex} > 0$ and $\delta_{mig} = \delta_{mex} - \delta_{us} > 0$, 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 of 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 household pool their income and have the same skill level. Households maximize a Stone-Geary utility function, which has the arguments c for consumption and d for the number of members who remain in Mexico. This implies the reasonable assumption that households prefer to have 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, $\underline{d}$. Including the minimum consumption level $\underline{c}$ is important for understanding the migrant supply function of households 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. We include the minimum number of household members in Mexico, $\underline{d}$, for two reasons. First, our data do not include Mexican households that move entirely to the United States. Second, including this variable is in line with recent literature that identifies weak property rights as an important barrier for household migration in Mexico (de Janvry, Emerick, Gonzalez-Navarro, and Sadoulet 2013).

We do not model household decisions in terms of labor and leisure; we focus only on their decisions to distribute labor between origin and destination labor markets. We abstract from intra-household allocation decisions and assume income pooling. This is not a restrictive assumption, since it suffices for results to hold that only a share of the household income comes from remittances from household members at destination, which is consistent with the empirical evidence (Hanson 2007; Yang 2011; Amuedo-Dorantes and Pozo 2012; Arango, Mata, and Obando 2015). We also normalize the price of the consumption good to 1. Under these assumptions, households optimally choose the quantity of labor supplied in the United States by solving the following maximization problem:

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

$$s.t.\ d \cdot (\mu_{mig} - \delta_{mig} \cdot s) + c \leq X, \text{ and } d \leq \bar{m}.$$

$X = \bar{m} \cdot (\mu_{mig} - \delta_{mig} \cdot s) + D(s)$ is income that a household would earn if it sent all its members to work in the United States, where $\bar{m}$ is the total amount of labor that a household can supply and $D(s)$ is the labor income at origin of a household 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 the m^* of households with $m^* > 0$ responds to changes in wages at destination 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 on skills remain unchanged.[5] 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 households have a sufficiently high level of labor income at home, the derivative has a positive sign. On the other hand, for households with low levels of s, meaning low levels of wages at origin, the derivative is negative. That is, for households with a low income at origin, negative shocks in the United States are followed by an increase in the number of individuals that leaves the household to supply further labor in the destination market.

After a negative employment shock at destination, the US labor market becomes relatively less attractive, triggering a substitution effect that pushes all households to reduce the amount of labor they supply in the United States. However, the reduction in wages at destination also makes households with migrants poorer, and this produces an income effect that leads to greater levels of migration (since labor at origin 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 households with a low income at origin the latter effect dominates, as the decrease in labor income at destination impacts their total budget in a way that jeopardizes their ability to meet the required minimum levels of consumption. By contrast, for higher-income households, the income effect is more moderate and the substitution effect dominates, leading them to substitute destination for origin work after the migration premium diminishes.[6]

3.1 Additional Considerations

Our simple model illustrates that households with different income or skill levels may react differently to an economic shock of a given magnitude at the destination. However, there are alternative theoretical mechanisms that emphasize other sources of heterogeneity across households with varying income or skill levels that, in principle, could also deliver similar empirical implications to those of our model. First, while our

[5] In Section 7 we address the implications of the assumption of homogeneous shocks across skill levels.

[6] Additionally, s^{max} is reduced after a decrease in μ_{mig}, meaning that the most skilled families (among those who found it optimal to send members abroad before the shock) find it optimal to bring all migrant workers home 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.

model assumes that the intensity of the unemployment shock is homogeneous for all households - irrespective of their income level - there is a possibility that it differs. If unemployment shocks were larger for high-income households, we would expect similar heterogeneous effects across income levels to those predicted by our model. Since this is an empirical concern, in Section 7, we deal empirically with the possibility that the test of our model's implications is confounded by heterogeneity in the magnitude of the unemployment shock across income/skill levels.

A second plausible source of heterogeneity across households with varying income or skill levels that we abstract from is on the costs of migrating. Information acquisition costs (Munshi 2003; McKenzie, Gibson, and Stillman 2013) and financial constraints (Angelucci 2015; McKenzie and Rapoport 2010) might vary across income or educational levels, being relatively low for individuals from high-income households, and may be prohibitively high for potential migrants from poor households. We argue, however, that this source of heterogeneity does not deliver similar empirical implications to those of our simple model. A migration cost structure as the one previously mentioned would lead to an overall lower responsiveness to labor-market shocks among low-income households. Specifically, it would imply that, when facing unemployment shocks at destination low-income households are both: i) less likely to bring back their migrant members from destination, and ii) less likely to send additional household members abroad. While the former prediction is also an implication of our simple model, the latter prediction is at odds with it. In our empirical analysis, we study the effects of unemployment shocks at destination on out-migration and return migration separately, and we are able to rule out that our results are accounted by a framework that abstracts from the income effect generated by unemployment shocks at destination, even when allowing for the heterogeneous migrating cost structure considered in the literature.

Finally, although our theoretical framework discusses wage changes, throughout our empirical work, we use changes in employment levels instead of changes in wages. Some authors have documented the fact that the period we are studying has been characterized by nominal wage rigidity in the United States, even during periods of very high levels of job destruction (see Cadena and Kovak (2016) for a discussion of this issue). Therefore the 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, multiplied by the probability of being employed, p_i. In this redefined framework, our empirical work would capture changes in p_i for a fixed W_i.

4 Measures, Data and Empirical Specification

4.1 Shock Measure

Our main treatment variable is the change in expected US unemployment, which we construct exploiting municipal patterns of past migration across different destinations in the United States and changes in employment conditions in those destinations.

To capture municipal patterns of past migration across different US destinations, we use survey data from the 1999 to 2003 waves of the EMIF Norte (Survey on Migration at the Mexican Northern Border).[7] 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 were asked about the Mexican municipality they resided in, whether they were planning to cross into the United States, and which city was their final US destination.

With this information, we construct origin-destination cells that capture Mexican municipality-specific measures of the geographical distribution of migrants in the United States. 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.[8]

We then estimate the expected unemployment of households in municipality m as the weighted average of the unemployment rates at US 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 Current

[7] We focus on the data from these waves for several reasons. First, the data from 2005 might be affected by the unemployment changes whose effect we study. Second, there was a change in the coding of destinations in the United States in 2004, which led us to drop the 2004 data for the sake of consistency in the coding. Third, data before 1999 are probably less accurate due to the more contemporary location of Mexican migrants from a municipality in a US destination. In addition, before 1999 the data were reported biannually, which led us to doubt whether there were also changes in the methodology used to collect the data.

[8] Due to data limitations, we abstract from the possibility of relocation by Mexican immigrants within the United States.

Population Survey (CPS) of the US Bureau of Labor Statistics,[9] and compute:

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

We then denote the change in expected US unemployment or shock received in households in municipality m as the year-to-year change in expected unemployment:

$$S_{m,t} = EU_{m,t} - EU_{m,t-1}.$$

While our measure of geographical distribution, $p_{m,d}$, is constant over time, our municipality-year specific shocks are time varying. We chose a yearly time framework because several specifications indicate that yearly unemployment rates at the metropolitan area level are highly persistent, and thus yearly changes in expected unemployment rates can be interpreted as unanticipated changes.

Note that we can only compute shocks for a given municipality if the EMIF Norte provides at least one individual intending to cross the border for which both the municipality of residence in Mexico and the desired American destination are known.[10] There is at least one migrant for 1,206 municipalities, which represent about half of all Mexican municipalities. For the average Mexican municipality in our sample of 12,012 observations, we observe 9.84 migrants.

The measure of expected unemployment rates we construct is informative of the households' actual received shocks as long as: 1) the location decisions in the United States for Mexican migrants are correlated within Mexican municipality over time, and 2) there is no full relocation of Mexicans in the United States after local labor market shocks. The location patterns of Mexicans in the United States widely support the first fact (Bauer, Epstein, and Gang 2002; Munshi 2003). Reallocation within the United States by Mexican migrants is also limited. In fact, Cadena and Kovak (2016) report that Mexicans display lower internal mobility in the United States than natives and other foreign-born populations. Despite the tough economic conditions of the 2006-

[9] In an alternative specification, we use Mexican-born (instead of overall) unemployment data at the same geographical level. See Section 6.2 for more detail.

[10] While we have data on the intended – but not the actual – destinations of migrants, we argue that these data provide a good measure of the traditional migration networks of migrants coming from the Mexican municipalities in the EMIF sample. First, intended destinations are defined at a fairly high level of aggregation (there are only 82 for the whole of the United States), which substantially reduces the possibility of measurement error. Second, the distribution of Mexicans in the United States according to their reported intended destination in the EMIF is similar to that of Mexican-born individuals in the 2010 US Census. Third, intended destinations convey important information about the location of traditional migration networks from specific Mexican municipalities, despite the migrants' final destinations.

2010 period, only 3% percent of Mexican migrants moved yearly within the United States.

Figure 1 presents the distribution of municipalities by the number of migrants observed in the EMIF. The fact that we construct the weights $p_{m,d}$ using relatively few observations of past migrants introduces some noise into our measure of the foreign unemployment shocks diffusing to Mexican municipalities. In Section 6, we further discuss the implications of this issue for our empirical exercise. As a robustness check, in some of our specifications we focus on municipalities that have more information on the geographical distribution of past migrants in the United States by restricting our sample to those with 10 or more migrants (269 municipalities meet these criteria). Accordingly, we divide Figure 1 into two panels: the top panel contains all municipalities that have 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.[11]

Figure 2 shows expected unemployment rates at destination in 2005 for all municipalities in our sample. Municipalities in the sample are distributed across Mexico, and there is significant variation in municipal expected unemployment at destination. Figure 3 illustrates changes in municipal expected unemployment rates at destination between 2005 and 2006, showing that our empirical strategy exploits significant variation in changes in expected unemployment at destination across Mexican municipalities.

Figure 4 presents the distribution of changes in expected unemployment rates at destination, pooling all Mexican municipalities and years in our sample. Such changes range 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, when most of the variation in our sample takes place, almost all of the expected unemployment changes experienced by Mexican households have a positive sign. Consequently, we consider our results to be especially informative in the context of increasing unemployment at destination.

4.2 Migration and Exposure Measures

We construct our migration outcomes using data 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 later moved to the United States.

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

Therefore the definition of migrant we use in this paper, which corresponds to that of the Mexican Census, is an individual who left her Mexican household and went to the United States after June 2005, irrespective of whether she remained abroad. For migrants, the year of the most recent trip to the United States is reported, as well as the year of the returning trip (if they 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 United States is for work-related reasons.[12] We use this information on migration to construct a panel at the household level with yearly information on migration events to and from the United States.[13]

From this data on migration we also construct an indicator variable, *exposed*, to capture whether a household had members living in the United States 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 the destination of households that have migrants in the United States relative to those that do not.

Our migration data present two main shortcomings, which we explain further in Appendix A and illustrate in Figures A1 and A2. First, the census only asked about an individual's last trip. Therefore, as indicated in Figure A1, if a person took multiple trips to the United States during the study period, we introduce two potential sources of measurement error: we miss the information regarding the individual's prior migration events, and potentially miscode her household as non-exposed during the years before she returns to Mexico.[14] Second, for individuals who left for the United States 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 1) assume that each individual had no more than one migration spell during the 2005-2010 period and 2) exclude households with *pre-2005 migrants*. However, in Section 6.3, we present two empirical strategies that partially deal with these two issues and show that our results are robust to these alternative specifications.

Once we match the migration data 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, for both the full sample (Panel A) and the

[12] Angelucci (2015) estimates from a sample of 506 Mexican villages that the share of international migration that was work related in 1998 was 85%.

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

[14] If the individual has additional household members in the United States, the household is correctly coded as exposed.

subsample of households that changed their exposure status at least once during the study period (Panel B). We observe 31,558 households changing their exposure status at least once (2.47% of the total sample). While this number may underestimate the true level of exposure, given some of our data limitations,[15] the figure is fairly consistent with the number of Mexican households that receive remittances from the United States (CONAPO 2005). The values of the variables for households with changing exposure status are within the ranges of the general population, although they are, on average, somewhat less educated and have lower incomes than the mean household of each quintile.

In Table 2 we compare the observable characteristics of EMIF migrants with those of adults in the households that changed their exposure status in the 2010 Mexican Census.[16] Migrants in the EMIF are similar to the adults in households with migrants captured by the census. The migrants in the EMIF are generally younger, have a slightly lower labor income (from their previous job), and are slightly more educated.

The Mexican Family Life Survey (MxFLS) and the Mexican Migration Project (MMP) are alternative data sources on migratory experiences of individuals in Mexican households. We are unable to use these datasets since, relative to the data from the 2010 Mexican Census that we use, the number of sampled municipalities are too few in both cases. Moreover, the few sampled municipalities have very few instances of migratory experiences. The third wave of the MxFLS, conducted between 2009 and 2012, contains information only for 368 instances of migratory experiences (of at least one year) to the US, coming from 310 individuals in 281 households (around 2.7 percent of the 10,125 surveyed households) in 94 municipalities.[17] More importantly, given our empirical strategy, there are only 21 municipalities with 5 or more households with migratory experience to the US. In contrast, our data contains analogous information for 1103 municipalities.[18] Similarly, the MMP conducts surveys only in a handful of communities every year. For the period we study (2005-2010), this data is even smaller

[15]Recall that we cannot capture households that fully moved to the United States or those with individuals who moved before 2005 but returned between 2005 and 2010, and for whom the return date is not reported. However, the Mexican households that fully moved to the United States during the 2005-2010 period, which we deem extremely few, should not affect our identification as long as full movements of Mexican households to the United States are uncorrelated with changes in municipal expected unemployment at destination. While we do not have the data on those households that would allow us to address such a correlation, omitted regressions suggest that changes in the municipal number of households between 2005 and 2010 are uncorrelated with changes in municipal expected unemployment at destination during the same period.

[16]We define adults as over 15 years old, the age of the youngest migrants in the EMIF.

[17]Without restricting the sample to the municipalities with at least one instance of migratory experience, the third wave of the MxFLS was spread among 288 municipalities, half of which have 5 or fewer observations. The original wave surveyed households in 136 municipalities.

[18]The number of municipalities in our sample is mostly restricted from the approximately 2,400 municipalities by the lack of information on the geographical location of previous migrants, and not by the absence of municipalities in the Census itself.

than the MxFLS, with only 52 communities interviewed since 2005.

4.3 Empirical Specification

Our baseline specification is:

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

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 United States at the beginning of year t. Note that *exposed* is a lagged variable, and as such, its value in year t depends on migration up to year $t-1$, and not on contemporaneous migration decisions. By doing this, we avoid any positive mechanical 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 $shock_{mt}$. 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 in which we include municipality-year fixed effects.

In most of our regressions, Y is a net migration index, taking a value of 1 if the household experiences positive net out-migration in year t, 0 if the household's net migration is neutral, and -1 when the household experiences positive net return migration. 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 United States, and β_1 represents the differential response of exposed vs. non-exposed households. Our main interest is in the latter. We also have a particular interest in the heterogeneity of such a differential response across income levels.

Economic shocks in the United States directly affect the income of exposed households, but not that of non-exposed households. An increase in US unemployment levels 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 United

States on exposed households relative to non-exposed ones should vary with the households' income levels. 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 by domestic labor income levels, namely, subdividing the sample by income quintiles.

Returning to β_0, information sharing is one channel through which non-exposed households might be affected by changes in expected unemployment in the United States. Consider a non-exposed household that lives in Mexican municipality m. Assume that most migrants from municipality m work in American city y. Because city y is a traditional destination of migrants from municipality m, information about the economic conditions in city y spreads in municipality m. Thus, if city y receives a negative economic shock, it could affect the decision of a non-exposed household in municipality m to send a migrant to the United States, since expected earnings abroad decrease. Thus, we would expect β_0 to be negative.

However, the information-sharing effect assumes that households primarily obtain information about economic shocks in the United States 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).[19] Thus, if other non-network-specific sources provide relevant information for migration decisions, it is less likely that our measure of shocks explains the migration decisions of non-exposed households.

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

Note 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 households, while driving higher-income/skill individuals back to Mexico. For heterogeneity in economic shocks

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

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 should, if anything, bias our empirical results against confirming the implications of our model. Moreover, in Section 7 we compute income-quintile specific shocks and show that our main findings remain unchanged.

5 Results

We begin by describing some features of our data in terms of observed migration of Mexican households by income quintiles. Figure 5 shows the annual US unemployment rate, as well as the yearly proportion of households with migrants coming from each income quintile during the 2006-2010 period. Figure 5 reflects that, as the economic conditions in the United States worsen, the relative share of migrants coming from the two lowest-income quintiles increases by over 6%, while the share of those coming from the top 40% in the income distribution falls by almost 5%. These trends suggest that negative shocks in the US 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 laid out in Section 4.

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, as previously discussed. While exposed households 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 households, which are directly affected by US economic conditions, to the unemployment shocks. Therefore, in all regressions we focus on comparing 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 United States 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 households. This is one of our key findings. In terms of our theoretical framework, the US shock triggers a large income effect for these exposed households, which consequently respond by increasing their number of migrants to the United

States with the purpose of compensating for their income loss.

Also consistent with our predictions, the estimate of β_1 decreases 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 households to reallocate their labor supply in favor of the domestic market after the negative shock in the United States 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 1 percentage point for exposed households in the lowest income quintile. The effect is slightly stronger for the top quintile group, but in the opposite direction.

Table 3 also shows that the estimates of β_0, which capture the effect of changing economic conditions in the United States for non-exposed households, are positive. While this result may seem somewhat puzzling, as it suggests that non-exposed households are more likely to move to the United States when expected unemployment at destination increases, our discussion in Section 4 suggests that the theoretically expected sign is ambiguous. Moreover, 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 magnitude reflects the fact that the migration decisions of exposed households are much more sensitive to US unemployment shocks than those of non-exposed households. Additionally, the estimates of β_0 are not robust across the different specifications.[20]

In Panel B of Table 3, we run regressions using the net number of migrants (the number of household members going to the United States minus the number of members going back to Mexico) as the dependent variable, instead of the index previously presented. The results are consistent with those of Panel A in Table 3 and with our model's predictions. 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 households in the lowest income quintile to increase their number of members in the United States by an average of 0.007 individuals. In the highest quintile, a shock of the same magnitude is associated with an average return of 0.016 migrants to the household.

[20]Our estimated coefficients for β_0 could also be partially capturing the fact that some households that are exposed appear as non-exposed in our sample.

In order to better understand what is driving our results, we perform separate analyses for out-migration and return migration. In Panel C of Table 3, we focus on out-migration. In these regressions, our dependent variable is a dummy taking a value of 1 when the household experiences positive net migration to the United States, and 0 otherwise. The results are very similar to those of Panel A of Table 3, where we use the migration index instead. Namely, exposed households in the lowest income quintile display 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 that high-income households will increase their labor supply in the United States.

In Table 3, Panel D we focus on return decisions. In this case, the dependent variable is a dummy taking a value of 1 when a household experiences positive net return migration. The results show that the returning decisions for high domestic income households are more sensitive to negative shocks in the United States than those of 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 United States translates into a negative migration premium for the high domestic earners.

In summary, our results are accounted for by the fact that deteriorating US labor market conditions lead to heterogeneous responses across domestic income quintiles in two dimensions: 1) the probability of sending additional migrants and 2) the probability that migrants will return.

6 Robustness Checks

We perform a series of robustness checks that we divide into 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.

6.1 Endogeneity and Measurement Error

We first address the fact that, since income is measured in 2010, this measure might be affected by the household's contemporaneous migration decisions. To alleviate this concern, we consider income quintiles by *predicted* income rather than reported income, where the fitted values are obtained from pre-determined variables: linear and quadratic household head's 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 quintile. For each household, we compute the average years of education of its adult members.[21] We consider this measure of household education level to be the closest to our theoretical framework, in which households 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 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 it 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 about our empirical strategy is related to the measurement of the municipality-specific geographical distribution of migrants in the United States. 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 Mexican municipalities 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 2015; Feigenberg 2013) show that changes in border enforcement have an important effect on migration rates from Mexico to the United States. This might be a concern for our strategy if the allocation of border patrol resources along the frontier is correlated with local labor market conditions in the United States. To address this issue, we identify 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

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

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

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

affect migrants from different municipalities differently.

We also consider the role played by recent migration rates in the household's origin municipality. If past migration is correlated with both the current probability of migrating and economic shocks at destination, it could bias our estimates of interest.[24] To control for this, we include the share of households from each income quintile in municipality m that experienced net positive migration in $t-1$ as additional regressors. We then run

$$Y_{imst} = \delta \cdot exposed_{it} + \beta_0 \cdot shock_{mt} + \beta_1 \cdot (exposed_{it} * shock_{mt})$$

$$+ \sum_{q=1}^{5} \gamma_q \cdot propY_{qmt-1} + \eta_i + \phi_{st} + \epsilon_{imst}, \tag{2}$$

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 be concerned that US unemployment shocks 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 differentially through income quintiles, as unemployment shocks do. Even though such a case is unlikely, we conduct a specification including municipality-year instead of state-year fixed effects. We then run

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

where β_0 disappears as it is subsumed by the municipality-year shock.[25]

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 households' responses to shocks across income levels. More specifically, the interaction term remains positive and significant for the lowest-income group and is decreasing in all cases. 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 regres-

[24] Borjas (2003), Card (1990, 2001), Friedberg and Hunt (1995), Manacorda, Manning, and Wadsworth (2012), and Ottaviano and Peri (2012) highlight the impact of past migration on the economic outcomes at destination.

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

sions, especially when we restrict the sample to municipalities with more migrants in the EMIF (Panel B).

6.2 Mexican-born Unemployment

For our baseline analysis, we construct labor market shocks in the United States using information on unemployment rates of both the Mexican and non-Mexican born population in the United States. While we could have instead restricted the analysis to the employment situation of the Mexican-born population in the United States, such a restriction produces a significantly smaller sample size and renders the measurement of the shocks less precise. Indeed, the cross-sectional standard deviation of the shock when measured using only Mexican-born individuals increases by a factor of around 10 with respect to our baseline shock.[26] 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 exhibit greater geographical mobility than natives (Cadena and Kovak 2016). Thus, using unemployment measures of the overall US population may bias our estimates because of rapid relocation decisions. To address this concern, we recompute unemployment shocks using the more restrictive CPS sample of Mexican-born population and re-estimate our baseline regressions. Note 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 United States. The main difference in this set of results is the smaller (in absolute terms) and insignificant coefficients for the higher-income group. We attribute this to the fact that the information contained in the CPS is more representative of 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 workers concentrate in agricultural production, construction, eating/drinking places, grocery stores, hotels, landscape/horticultural services, meat products, private households, services to dwellings, and trucking services.

[26]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 a benefit.

6.3 Migration Data

Our migration data from the Mexican Census present two main shortcomings. First, by exclusively reporting the last trip of each migrant, it prevents us from identifying repeated trips of individuals who migrate to the United States multiple times during our period of analysis. In our empirical analysis, we have no choice but to neglect this problem, which generates measurement error in our outcome variables and potentially the exposed household variable. It is not evident how this biases our results, if at all. 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 and compute the municipal share of migrants to the United States who report a previous migratory trip within 5 years.[27] We then exclude from the regression those municipalities with shares of repeated migrants above the median.

A second concern stemming from the census data on migration is that data on the year of the return of those individuals who migrated to the United States before June 2005 and returned to Mexico between 2005 and 2010 are missing. In our previous specifications, we exclude households that have migrants in that situation. To address how such a sample restriction affects our results, we estimate our baseline equation including those households. To do this, we estimate the missing return year of the *pre-2005 migrants* using household observable characteristics. In a first step, we use the households with migrants between 2005 and 2007 and estimate a multinomial logit of length of stay (in years) on a set of observable household 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 similar households have US migration spells of similar duration regardless of when they left and the shocks they faced. While such an assumption might introduce some noise, we obtain extra information from the 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 return date 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 responses across income quintiles becomes starker, with the three highest quintiles showing a significant negative term for the interaction.

[27] 7.1% of migrants meet this criterion in the median municipality.

7 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 1) the unemployment shocks received by households and 2) moving costs.

7.1 Heterogeneous Unemployment Shocks

In our baseline analysis, we assume that municipality-year specific economic shocks at destination are common across households that belong to different income quintiles. However, there is the possibility that labor market shocks are heterogeneous across households with different incomes. This introduces the concern that our results may arise from variation in how our common unemployment shock measure correlates with the actual shock received by migrants from different income groups. We perform two exercises that rule out such a concern.[28]

Our aim in this section is to construct income-quintile specific shocks. To do this, we first exploit the fact that the presence of Mexican migrants in different US industries varies across the income distribution of Mexican households. To determine the Mexican income quintile to which each migrant worker in the United States belongs, we assume that Mexican migrants in quintile q of the wage distribution of Mexican-born individuals working in the United States 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 quintile according to their wage distribution in the United States. 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 income quintile-year-destination using industry-specific unemployment rates at destination from the CPS December wave of each year.[29] We then follow the same strategy described in Section 4 to compute

[28]The model in Section 3 suggests that changes in relative market opportunities are the key drivers of migration. However, our analysis only focuses on changes in employment opportunities at destination. There could then be the concern that changes in market opportunities at home are negatively correlated with those at destination within income quintiles. While this is highly unlikely, by dividing our sample according to income quintiles at destination and including state-year or municipal-year fixed effects, we largely control for changes in labor market opportunities across income quintiles in Mexico.

[29]The larger sample size of the ACS data allows us to estimate the industry compositions more accurately than if we were using the data from the CPS. However, we did not use the ACS data to construct quintile-specific unemployment shocks, since these data only provide annual averages of

the unemployment shocks received by Mexican municipalities, except that 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.[30]

As an alternative way to construct income quintile-specific shocks, we exploit variation in unemployment shocks at destination arising from differences in the geographic distribution of migrants from different income levels within each origin municipality. We consequently compute quintile-specific origin-destination matrices instead of simply origin-destination ones, as in our baseline specification. We exploit the fact that EMIF respondents also report their education level. Using information from the 2010 Mexican Census, we compute the average income of a household from Mexican municipality m with x years of education.[31] We then impute to each observation in the EMIF its expected income, and split the sample by quintiles. This way, for a given municipality of origin, we potentially have five origin-destination matrices, one for each income quintile.[32] Finally, we compute the municipality-quintile-specific shocks using the same strategy described in Section 4.

We present the results of this exercise in Table 5, which again shows the main features we observe in our baseline specification. They provide additional evidence that our baseline empirical estimates are not the product of heterogeneity in unemployment shocks across households with different incomes.

7.2 Heterogeneous Costs of Moving

As we discussed in Section 3.1, an explanation of migratory movements based on heterogeneous migration costs would predict relatively lower return migration among migrants from low-income households when exposed to negative labor-market shocks at destination. This prediction is indeed in line with our results on return migration in

unemployment because it is an annual survey. 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 (published monthly) to construct quintile-specific unemployment shocks.

[30]We also conducted the exercise by education quintiles instead of income quintiles, and found qualitatively similar results.

[31]We use the household head education.

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

Panel D in Table 3.

However, our findings on out-migration in Panel C in Table 3 are impossible to reconcile with a model that only has heterogeneous costs of migration across income levels. This heterogeneity in costs provides no rationale for low-income households in Mexico to send additional household members to the United States when employment conditions worsen at the destination. However, we observe that unemployment shocks at the destination lead to increased out-migration by low-income households. Therefore, a framework that abstracts from the role played by the income effect that households with members abroad face when negative labor-market shocks at destination affect those members cannot account for all of our results, even when allowing for the heterogeneous migrating cost structure considered in the literature.

8 Conclusion

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

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 households upon shocks. For exposed low-income households, a shock at destination has a sizable impact on their budget, triggering a large income effect. The households compensate this income loss by sending additional members to work in the United States. Conversely, for exposed high-income households, the substitution effect dominates and they reduce their migration rate when the migration premium decreases.

Our results help us understand 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 informs the literature on selection patterns in migratory flows. The effect of destination labor market 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, and increase the number of low-skilled individuals coming from already exposed households. This channel is traditionally ignored in the literature.

Our results also have implications for issues regarding development and poverty. According to our framework, the response of exposed low-income households 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.

References

Amuedo-Dorantes, C. and S. Pozo (2012, October). Remittance Income Volatility and Labor Supply in Mexico. *Southern Economic Journal 79*(2), 257–276.

Angelucci, M. (2015, March). Migration and Financial Constraints: Evidence from Mexico. *The Review of Economics and Statistics 97*(1), 224–228.

Antman, F. M. (2013). The impact of migration on family left behind. In *International Handbook on the Economics of Migration*, Chapters, Chapter 16, pp. 293–308. Edward Elgar Publishing.

Arango, L., D. Mata, and N. Obando (2015, November). Echoes of the crises in Spain and US in the Colombian labor market: a differences-in-differences approach. *SERIEs: Journal of the Spanish Economic Association 6*(4), 441–477.

Bauer, T. K., G. S. Epstein, and I. N. Gang (2002, August). Herd Effects or Migration Networks? The Location Choice of Mexican Immigrants in the U.S. IZA Discussion Papers 551, Institute for the Study of Labor (IZA).

Bohn, S. and T. Pugatch (2015, October). U.S. Border Enforcement and Mexican Immigrant Location Choice. *Demography 52*(5), 1543–1570.

Borjas, G. (1991). Immigration and self-selection. In *Immigration, Trade, and the Labor Market*, pp. 29–76. National Bureau of Economic Research, Inc.

Borjas, G. J. (1987). Self-selection and the earnings of immigrants. *American Economic Review 77*(4), 531–53.

Borjas, G. J. (1994). The economics of immigration. *Journal of Economic Literature 32*(4), 1667–1717.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics 118*(4), 1335–1374.

Borjas, G. J. and S. G. Bronars (1991). Immigration and the Family. *Journal of Labor Economics 9*(2), 123–48.

Borjas, G. J. and R. M. Friedberg (2009). Recent trends in the earnings of new immigrants to the United States. *NBER Working Papers*.

Bryan, G., S. Chowdhury, and A. M. Mobarak (2014, 09). Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh. *Econometrica 82*, 1671–1748.

Cadena, B. C. and B. K. Kovak (2016, January). Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession. *American Economic Journal: Applied Economics 8*(1), 257–290.

Card, D. (1990). The impact of the mariel boatlift on the miami labor market. *Industrial and Labor Relations Review 43*(2), 245–257.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics 19*(1), 22–64.

Chiquiar, D. and G. H. Hanson (2005). International migration, self-selection, and the distribution of wages: Evidence from Mexico and the United States. *Journal of Political Economy 113*(2), 239–281.

Chiquiar, D. and A. Salcedo (2013). Mexican migration to the United States. underlying economic factors and possible scenarios for future flows. Technical report, Migration Policy Institute.

Clark, X., T. J. Hatton, and J. G. Williamson (2007). Explaining US immigration, 1971-1998. *The Review of Economics and Statistics 89*(2), 359–373.

de Janvry, A., K. Emerick, M. Gonzalez-Navarro, and E. Sadoulet (2013). Delinking land rights from land use: Certification and migration in mexico.

Dessing, M. (2002). Labor supply, the family and poverty: The S-shaped labor supply curve. *Journal of Economic Behavior & Organization 49*(4), 433–458.

Dustmann, C. (2003). Return migration, wage differentials, and the optimal migration duration. *European Economic Review 47*(2), 353–369.

Farré, L. and F. Fasani (2013). Media exposure and internal migration: Evidence from Indonesia. *Journal of Development Economics 102*(C), 48–61.

Feigenberg, B. (2013). Fenced out: Why rising migration costs matter. *Working Paper*.

Fernández-Huertas Moraga, J. (2013). Understanding different migrant selection patterns in rural and urban Mexico. *Journal of Development Economics 103*(C), 182–201.

Friedberg, R. M. and J. Hunt (1995). The impact of immigrants on host country wages, employment and growth. *Journal of Economic Perspectives 9*(2), 23–44.

Gibson, J. and D. McKenzie (2014, May). The Development Impact of a Best Practice Seasonal Worker Policy. *The Review of Economics and Statistics 96*(2), 229–243.

Gibson, J., D. McKenzie, and S. Stillman (2011, November). The Impacts of International Migration on Remaining Household Members: Omnibus Results from a Migration Lottery Program. *The Review of Economics and Statistics 93*(4), 1297–1318.

Grogger, J. and G. H. Hanson (2011). Income maximization and the selection and sorting of international migrants. *Journal of Development Economics 95*(1), 42–57.

Hanson, G. H. (2007). Emigration, remittances and labor force participation in Mexico. Intal working papers, Inter-American Development Bank, INTAL.

Lessem, R. (2013). Mexico-US immigration: Effects of wages and border enforcement. *Working Paper*.

Lundberg, S. (1985). The added worker effect. *Journal of Labor Economics 3*(1), 11–37.

Maloney, T. (1987). Employment Constraints and the Labor Supply of Married Women: A Reexamination of the Added Worker Effect. *Journal of Human Resources 22*(1), 51–61.

Manacorda, M., A. Manning, and J. Wadsworth (2012). The impact of immigration on the structure of wages: Theory and evidence from Britain. *Journal of the European Economic Association 10*(1), 120–151.

Mayda, A. (2010). International migration: A panel data analysis of the determinants of bilateral flows. *Journal of Population Economics 23*(4), 1249–1274.

McKenzie, D., J. Gibson, and S. Stillman (2013). A land of milk and honey with streets paved with gold: Do emigrants have over-optimistic expectations about incomes abroad? *Journal of Development Economics 102*(C), 116–127.

McKenzie, D. and H. Rapoport (2010). Self-selection patterns in Mexico-US migration: The role of migration networks. *The Review of Economics and Statistics 92*(4), 811–821.

McKenzie, D. and H. Rapoport (2011, October). Can migration reduce educational attainment? Evidence from Mexico. *Journal of Population Economics 24*(4), 1331–1358.

McKenzie, D., C. Theoharides, and D. Yang (2014, April). Distortions in the International Migrant Labor Market: Evidence from Filipino Migration and Wage Responses to Destination Country Economic Shocks. *American Economic Journal: Applied Economics 6*(2), 49–75.

Mincer, J. (1978). Family migration decisions. *Journal of Political Economy 86*(5), 749–73.

Munshi, K. (2003). Networks in the modern economy: Mexican migrants in the u.s. labor market. *The Quarterly Journal of Economics 118*(2), 549–599.

Ottaviano, G. I. P. and G. Peri (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association 10*(1), 152–197.

Parker, S. and E. Skoufias (2004). The added worker effect over the business cycle: Evidence from urban Mexico. *Applied Economics Letters 11*(10), 625–630.

Passel, J., D. Cohn, and A. González-Barrera (2012). Net migration from Mexico falls to zero - and perhaps less. Technical report, Pew Hispanic Center Report.

Roy, A. (1951). Some thoughts on the distribution of earnings. *Oxford Economic Papers* (3), 135–46.

Schnabl, P. (2007). Migration and development in mexican communities: Evidence from us labor demand shocks. *Working Paper*.

Stephens, M. (2002). Worker displacement and the added worker effect. *Journal of Labor Economics 20*(3), 504–537.

Yang, D. (2008, 04). International Migration, Remittances and Household Investment: Evidence from Philippine Migrants' Exchange Rate Shocks. *Economic Journal 118*(528), 591–630.

Yang, D. (2011). Migrant remittances. *Journal of Economic Perspectives 25*(3), 129–52.

Appendix A: Data (For Online Publication)

A.1 Origin-Destination Cells

The EMIF Norte is designed to measure the migration flows to and from Mexico across its northern border with the United States. The sampling design (the final goal of which is to draw conclusions about the total flow of migrants) consists of defining time-place slots in the Mexican border cities to interview 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 destinations in this database is tallied at the state level, but for 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 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 United States during the study period.

2. Individuals who were living in Mexico in June 2005 and moved to the United States at some point during the study period, irrespective of whether they returned to Mexico. This is our definition of *migrant*. For each of these individuals, information on the month and year of their trip to the United States is reported, as well as the month and year of their return (if applicable).

3. Individuals who were living abroad in June 2005 and had returned to the household by the time of the census. We call these *pre-2005 migrants*. For these individuals, no information on the date of their 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 return trip. Therefore, in our baseline, we restrict our sample to households with no *pre-period migrants*, which drops around 3% of the sample. Additionally, individuals who were living abroad by June 2005 and had not returned to the household by the time of the census are not captured. In Section 6.3, we conduct a robustness check to show that our results are not sensitive to these data limitations and the sample restriction we impose in our baseline analysis.

Additional issues: As in most data sets used for studies on migration, we lack information on households that moved entirely to the United States during the 2005-2010 period. As mentioned above, we deem the number of Mexican households that fully moved to the United States during our period of analysis to be extremely small and significantly smaller than in previous years. Moreover, as long as full movements of Mexican households to the United States are uncorrelated with changes in municipal expected unemployment at the destination, their presence should not affect our identification. While we cannot test for such a correlation, changes in the municipal number of households between 2005 and 2010 are uncorrelated with changes in municipal expected unemployment at the destination during the same period. This is an imperfect, but comforting, test.

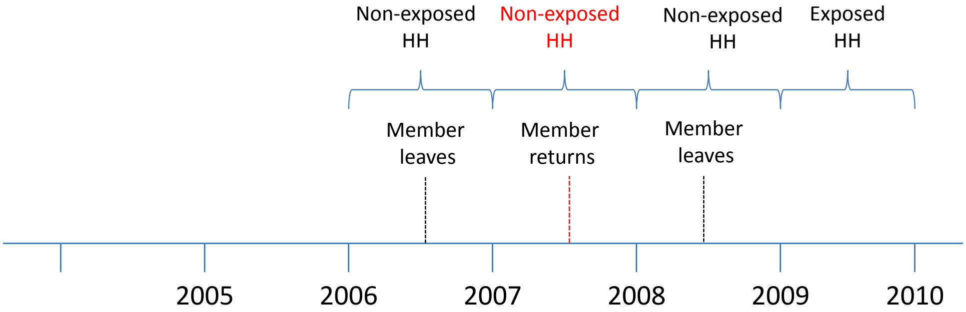

Figure A1: Individual with multiple trips
Example case: A migrant leaves for the United States during 2006, returns to Mexico in 2007 and goes back to the United States in 2008, where she remains until the end of the period. Since the census provides no information on the first trip, in our baseline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

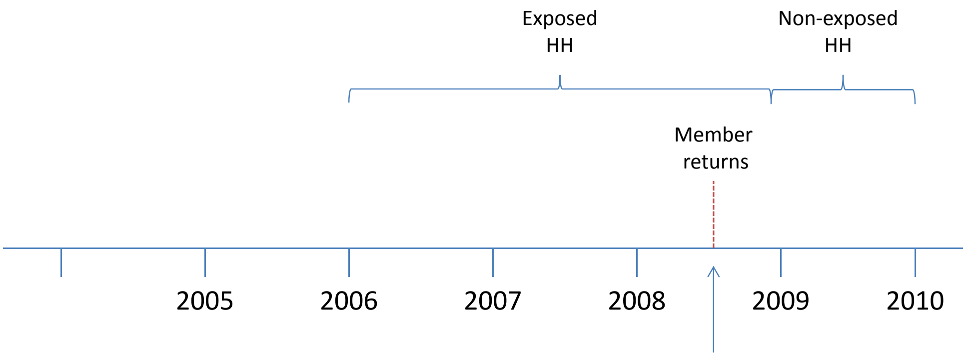

Figure A2: Pre-2005 migrants
Example case: A migrant leaves for the United States before 2005 and returns to Mexico during 2008. In this case, the census provides no information on the date of return. Therefore we have no information on the actual years the household was exposed. We drop these households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

Appendix B: Figures and Tables

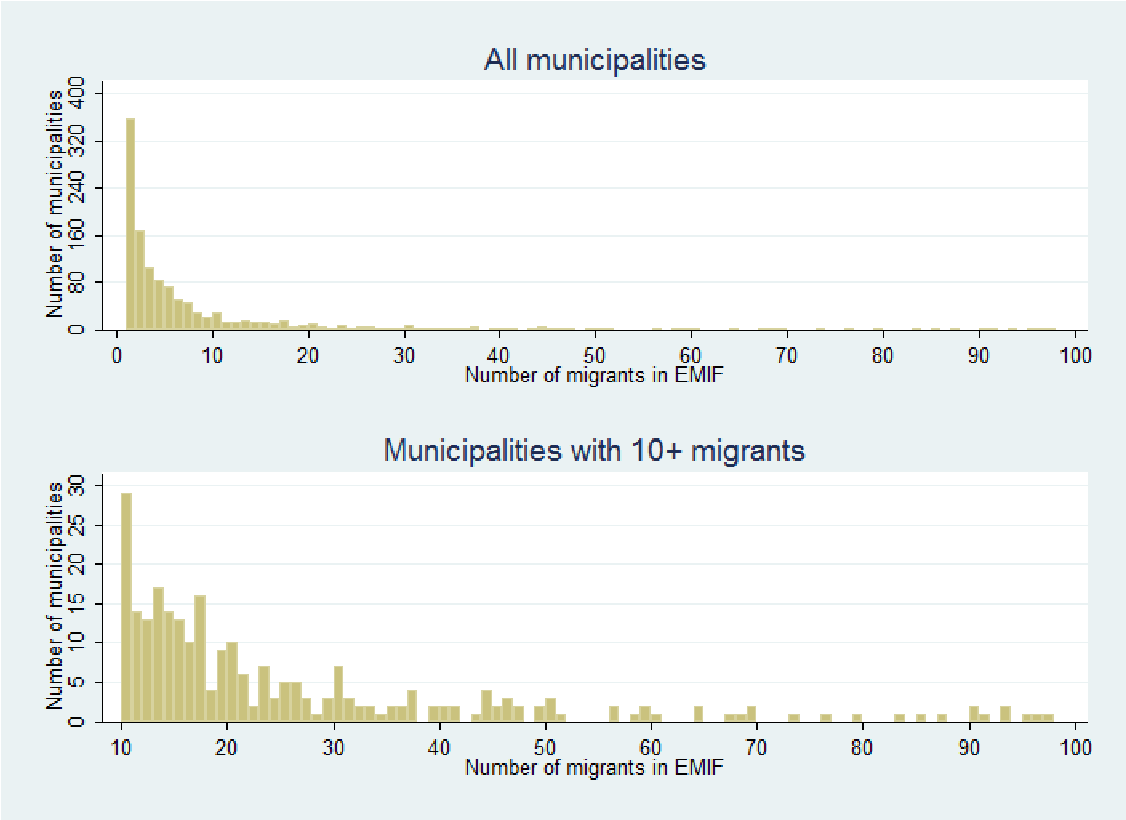

Figure 1: Distribution of Municipalities by Number of Observed Migrants in EMIF. For better visualization, we exclude 12 municipalities that have more than 100 migrants.

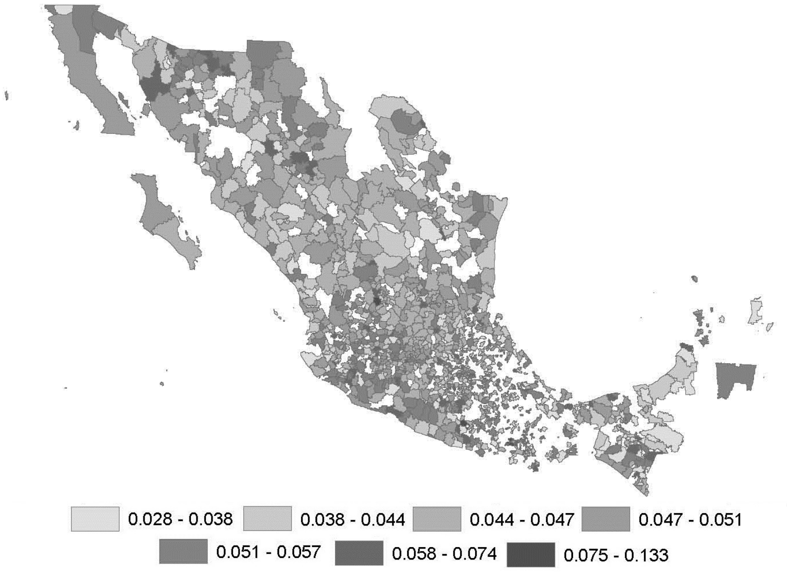

Figure 2: Expected Unemployment at the Destination in 2005

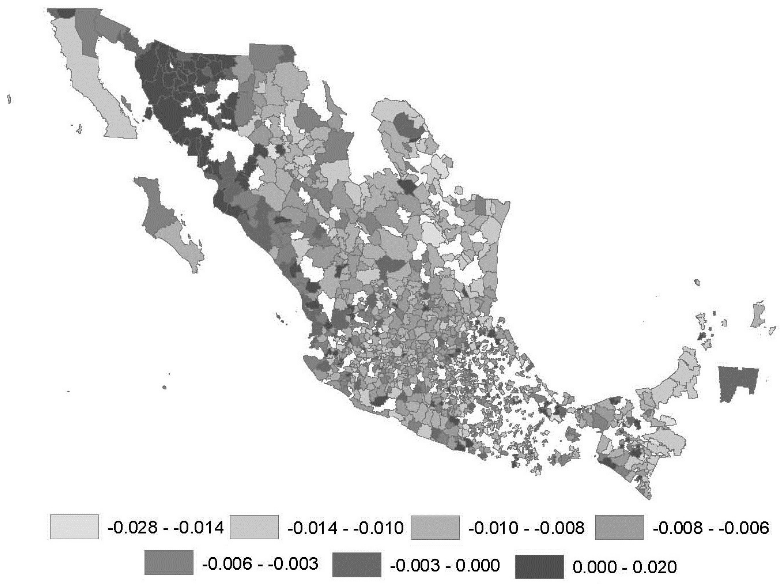

Figure 3: Change in Expected Unemployment at the Destination 2005-2006

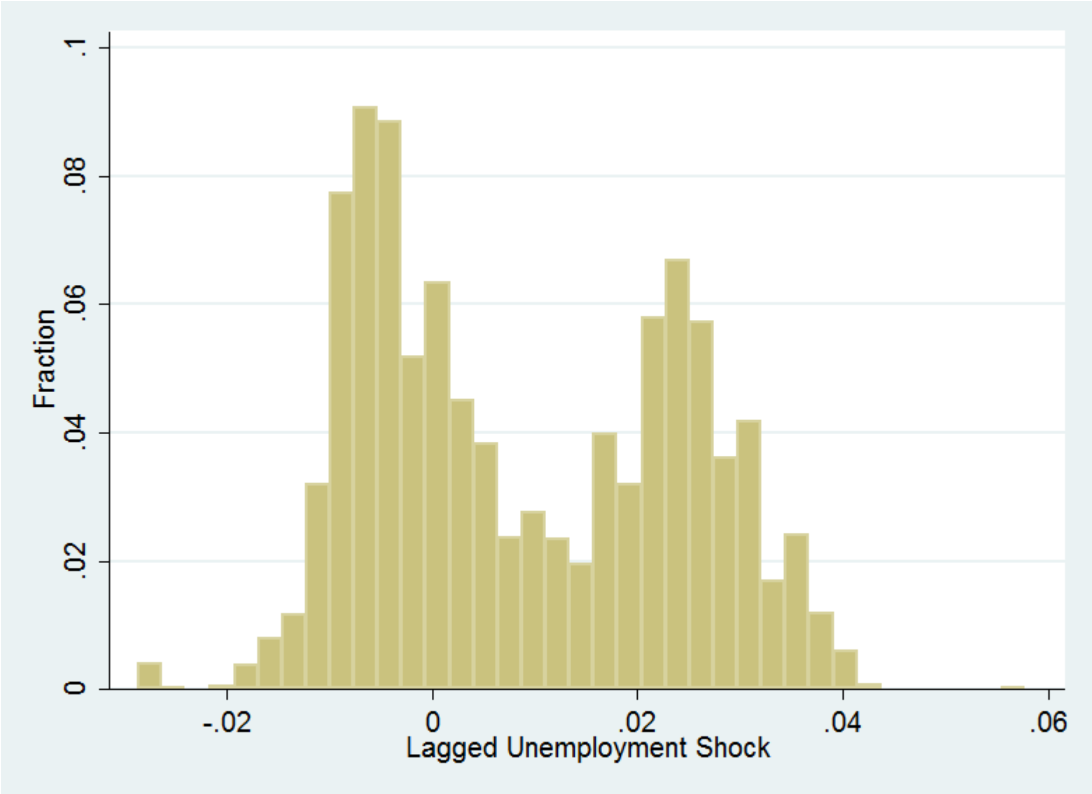

Figure 4: Distribution of Unemployment Shocks

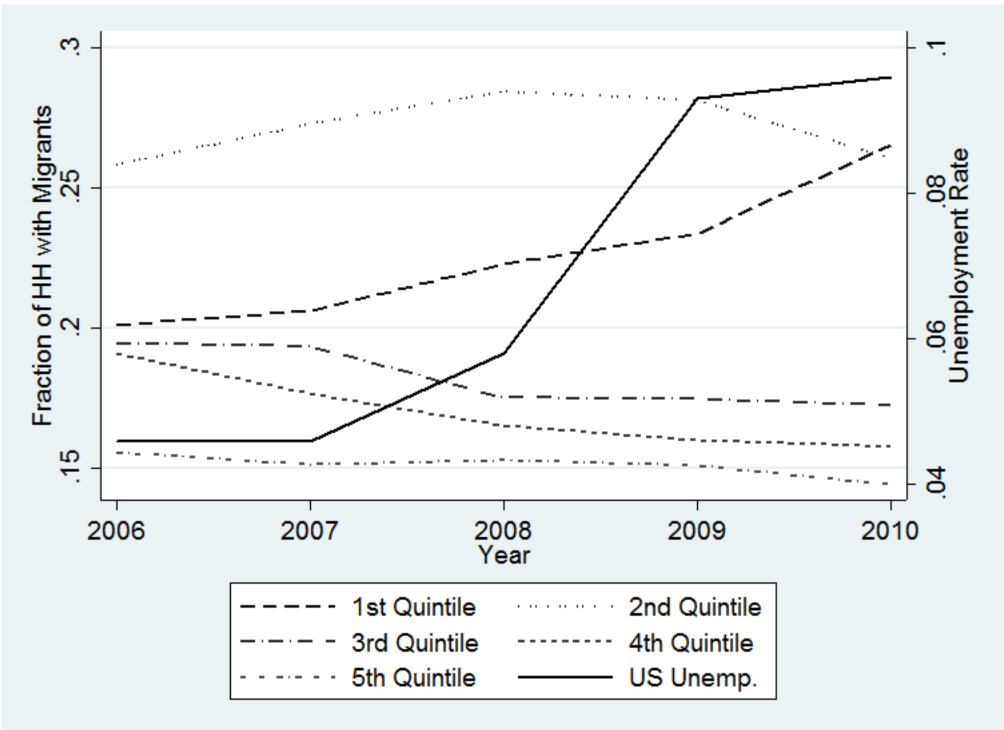

Figure 5: US Unemployment and Migration Rates by Income Quintile

Table 1: Summary Statistics by Income Quintile

	Income Quintile					
Variable	1	2	3	4	5	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: The unit of 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 the Census Sample of Adults from Households with Migrants 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 as 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 calculate as monthly values. The number of members of 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 who remain in the United States.

Table 3: Effect of Shocks on Migration Outcomes

Income quintile	1	2	3	4	5
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					
shock	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 observation is the household-year. We include household and state-year fixed effects, and 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 expected US unemployment. 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	1	2	3	4	5
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					
shock	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 observation is the household-year. We include household and municipality-year fixed effects, and 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 expected US unemployment, taking into account heterogeneity in the industry composition of Mexican workers across income levels. The 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	1	2	3	4	5
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 B. 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 C. 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 D. Return Migration					
shock	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 observation is the household-year. We include household and municipality-year fixed effects, and 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 expected US unemployment, 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 (Only Mexican-born Individuals Considered for Shock Calculation)

Income quintile	1	2	3	4	5
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 B. 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 C. 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 D. Return Migration					
shock	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: The unit of observation is the household-year. We include household and municipality-year fixed effects, and 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 expected US unemployment, constructed from the Mexican-born unemployment rate in 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 (For Online Publication)

Table C1: Number of Mexican-born Individuals Residing in the United States by Census Year

		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 Mexican-born individuals relative to other immigrant groups in terms of the 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 US Census Bureau's 2010 ACS.

Table C2: Geographic Distribution of Mexicans in the United States 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 individuals is from the US Census Bureau, 2010 ACS. (2) Data on the number of Mexican-born individuals as the share of the total population as of 2005 is from the US Census Bureau, 2005 ACS. *The value of the variable for this metropolitan area is estimated using the proportion of foreign-born individuals as a share of the population in the metropolitan area multiplied by the national average of Mexican-born individuals as a share of the foreign-born ones.

Table C3: Effect of Shocks on Net Migration Index

Quintile	1	2	3	4	5
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: The unit of observation is the household-year. We include household and state-year fixed effects, and 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 expected US unemployment. In Panel A, income quintiles are defined at the state level using predicted income from household head age (and its square), household head education level (and its 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	1	2	3	4	5
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. Controlling 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: The unit of observation is the household-year. We include household and state-year fixed effects, and 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 expected US unemployment. 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	1	2	3	4	5
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: The unit of observation is the household-year. We include household and municipality-year fixed effects, and 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 expected US unemployment. Income quintiles are defined at the state level using reported income. *** p<0.01, ** p<0.05, * p<0.1.