Risk of deportation and location decisions of Mexican migrants in the United States

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Abstract

Interior immigration enforcement in the United States has increasingly become jurisdiction of local authorities. This regulatory transformation has increased the variability of deportation risk across locations. In this paper, I include deportation risk in the ex-ante location decision problem of potential Mexican migrants and deportation shocks in the ex-post locations of migrants. Wage differentials, border patrol enforcement, and ethnic enclaves are also included as migration determinants. I first construct a measure of local deportation risk from a representative survey of deported Mexican individuals for the period 1998-2013. Counterfactual results using the Mexican Migration Project show that local deportation risk does not significantly affect the location decision of new migrants. This decision is primarily driven by the historical ethnic enclave of the migrants source community. Finally, I conclude that the elasticity of the international migration rate with respect to deportation risk is substantially smaller than the elasticity with respect to wages.

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1 Introduction

Immigration has been at the center of the political debate of the United States for decades. Historically, immigration policy was defined by federal authorities. However, there has been a recent change with respect to the regulation and enforcement of immigration laws. Recently, the role of local law enforcement as a regulator of immigration has grown substantially.[1]

This leading role of local authorities has increased the variation in immigration enforcement across states. For example, many states have enacted employment verification ("E-Verify") mandates to verify if employees have legitimate authorization to work in the U.S.[2] Some states, like Alabama, Arizona, and Georgia, have required that all public and private employers verify the status and eligibility of their workers. In contrast, states like California and Illinois have fought against the use of "E-Verify". The state of Illinois tried without success to prohibit employers from using "E-Verify" in 2008; the state of California passed a law to prohibit municipalities from mandating the use of "E-Verify" in 2011.

Another example of the growing role of the states in immigration enforcement is Section 287(g) agreements. Ever since the enactment of the Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA) in 1996, the Attorney General has permission to enter into enforcement agreements with state and local law agencies. With the 287(g) program, state and local policemen receive training to turn over any criminal immigrant to the U.S. Immigration and Customs Enforcement (ICE) agency. Watson (2013) documents that there were 68 local agencies in 23 states that were currently in agreements with ICE in 2011.

At the same time, the number of deportations has dramatically increased during the last two decades. By 1995, the total number of deportations was 50,924. By 2008, that number had increased to 358,886, which is more than six times the level observed in 1995 (Hagan et al., 2010). Additionally, the composition of the deported population has also changed. Settled migrants that have been in the U.S. for a number of years have become increasingly susceptible to deportation. Prior to 1996, most removals were at ports of entry.

Due to the growing number of deportations, changes in immigration regulation and recent proposals regarding immigration policy, it is important to understand the effects of different immigration and deportation policies on the behavior of undocumented and legal migrants. In this paper, I contribute to the understanding of the implications of these policies by analyzing the effect of deportation risk on the location choices of migrants. I focus on Mexican migrants to the U.S., who represent the main source of undocumented migration in the U.S. I do this analysis for the years 1998-2013, period in which local enforcement expanded and variation in

[1] In 2009 state legislatures passed 333 immigration-related pieces of legislation, compared to 38 in 2005. Regarding employment of immigrants, in the period 2005-2009, 91 laws were enacted in 34 states. (Bohn et al., 2014)

[2] "E-Verify" was created in 1997. This internet-based program is free and is operated by the Department of Homeland Security. "E-Verify" compares the information of an employee's "Form I-9" with data from the U.S. government records.

deportation across locations increased.

The structure of the paper is as follows. In Section 2, I present the main findings of the literature about the determinants of location choice of migrants that I will include in my assumptions. Also, I summarize the main findings of the few papers that have analyzed the effect of local immigration policies on the location of migrants. Finally, I relate my paper with the broader literature of selection of migrants.

In order to provide policy recommendations and study the effects of counterfactual immigration policies, in Section 3 I build a model where potential Mexican migrants decide whether to migrate to the U.S. or stay in Mexico. In contrast to most other papers that have previously analyzed the effect of stricter border patrol enforcement on migration patterns, I expand the analysis by allowing individuals to choose a specific location in the U.S. Also, I allow individuals to include the risk of deportation associated with each location as an important element to consider while maximizing his expected utility. This risk not only inflates the implicit migration cost of moving for undocumented migrants, but also introduces heterogeneity in the preference shocks across locations and time.

An additional contribution of the paper is to build a measure of deportation risk that is quantifiable and that allows me to conclude that the recent changes in immigration enforcement have actually affected the probability that an individual gets deported across locations. This is challenging due to the lack of reliable data on the number of undocumented migrants across locations. Even though the measure I construct might have substantial measurement error, it represents a first attempt to quantify a phenomenon that has been difficult to measure so far. I present this measure of deportation risk and the main datasets that I use in the rest of the paper in Section 4.

In Section 5 I present the estimation strategy that I follow to adapt the model to the data. Even though the model is static, there is not a closed form expression for the likelihood of the choice location. Thus, I proceed to use Simulated Method of Moments to find the estimates of the model parameters. Given all the model assumptions and parametrizations defined in Section 5, I present the baseline estimates of the parameters in Section 6.

The main takeaways of the paper can be found in Section 7, where I do four different counterfactual policies. Exploiting the structure of the model, I find that the variation of deportation risk across locations seems to have a negligible effect on location decisions. Additionally, I find that the international migrate rate seems to be fairly inelastic with respect to deportation risk. In contrast, potential migrants are substantially more sensitive to changes in wage differentials. Finally, in Section 8 I expand on the main conclusions of the paper.

2 Literature review

One of the seminal papers that studies the location of legal immigrants in the U.S. is Bartel (1989). The author uses a multinomial framework to conclude that immigrants are more geographically concentrated than U.S. citizens and live in cities with a big ethnic population. Additionally, the paper points out that education plays a key role in the location decision. In particular, workers with more education are less likely to be in locations with large ethnic populations and more likely to move to different locations after their arrival in the U.S. In this paper, I incorporate the findings of Bartel (1989) about the relevance of educational attainment and past immigrant population across U.S. locations to the decision of where to settle of new migrants.[3] Expanding on Bartel (1989), I also consider the margin of who moves from the sending country to the receiving country in the model.

However, in contrast to Bartel (1989), the main objective of this paper is to analyze the effects of immigration policies on the location decision of migrants. Even though immigration policies have been at the center of political debate for many decades, there are a relatively small number of articles that have analyzed the effect of immigration policies of receiving countries on migration flows and migrants' outcomes. Of these articles, most have only focused on border patrol enforcement. In particular, Angelucci (2012), Hanson and Spilimbergo (1999), Lessem (2017), and Thom (2010) stand out as recent relevant examples of this literature. The main takeaway of these papers is that border enforcement not only affects the incentives to migrate to the destination country, but also the incentives to return to the sending country. In particular, higher border enforcement is associated with an increase in the duration of trips of Mexican migrants in the U.S.

Due to the lack of research on deportation policy and immigration policy at the local level, the implications of variation in the risk of deportation on the outcomes and behaviour of new and settled undocumented migrants are currently not understood. Nonetheless, there are some papers that have studied the effects of immigration policies and deportation risk in a reduced-form approach, which indicate that immigration policies at the state level are relevant to understand the observed migration patterns in the U.S. data.

Amuedo-Dorantes et al. (2013) and Bohn et al. (2014) analyze the effect of the establishment of "E-Verify" systems on migration patterns. Amuedo-Dorantes et al. (2013) uses a cross-sectional survey of migrants travelling through the Tijuana-San Diego border region to document that the "E-Verify" mandates have increased the fear of deportation among Mexican migrants. The authors use a difference-in-difference approach, where the treated group is comprised by all the individuals that reside in states that have enacted some version of an "E-Verify" mandate. This increase in deportation risk, in turn, has lowered interstate

[3] Other important papers that have analyzed the relevance and effect of social networks and ethnic enclaves in migration outcomes are Munshi (2003) on occupation decisions of Mexican undocumented migrants in the U.S., and Edin et al. (2003) on labor market outcomes of refugees in Sweden.

mobility among voluntary returnees during their last U.S. trip and reduced the intent to go back to the U.S. of recent deported individuals. Bohn et al. (2014) quantifies instead the specific impact of the enactment in 2008 of the Legal Arizona Workers Act (LAWA) in Arizona, which has been one of the most severe pieces of legislation in terms of combating firms from employing undocumented migrants.[4] Using synthetic control methods, the article documents that the enactment of LAWA caused a reduction of 1.5-2.0% in the proportion of the Hispanic non-citizen population in Arizona during 2008-2009.

Parrado (2012) and Watson (2013) analyze the effects of the establishment of 287(g) programs on the geographic location of immigrants. Parrado (2012) finds that there is no direct impact of the establishment of a 287(g) program on the number of Mexican migrants except for four influential outliers: Dallas, Los Angeles, Riverside, and Phoenix. In contrast, Watson (2013) concludes that the 287(g) task force agreements spur migrants to move to a new Census division or region within the United States. The authors find that the effect is higher for migrants with a high level of educational attainment. However, the agreements do not deter cross-border migration flows. By focusing on deportation risk, computed directly from deportation statistics, and by building on a structural model, this paper will try to shed light on the mechanisms behind the recent results presented on Amuedo-Dorantes et al. (2013), Bohn et al. (2014), Parrado (2012), and Watson (2013).

Furthermore, this paper is also related to the literature on the selection of migrants which started with Borjas (1987). Although this paper currently does not study selection on unobservable traits, it does include selection on observable characteristics like education. In this sense, my paper expands on Chiquiar and Hanson (2005), and Kaestner and Malamud (2014) which observe patterns on intermediate selection based on education of Mexican immigrants in the U.S. I find that, at least in a static environment, a higher deportation risk is associated with migrants with (marginally) more education attainment. This result is driven by the fact that legal workers have on average more education than undocumented workers, and that a higher deportation risk (marginally) increases the proportion of migrants that are legal.

Finally, this paper also builds on the vast literature on internal migration. The classical determinant behind internal migration decisions has been local wage differentials. I find evidence of the relevance of wage differentials in migration decisions. Nonetheless, in this article I consider that migrants also give importance to other local amenities, as modelled recently by Diamond (2016) and other papers. In particular, deportation risk or local immigration policies might be an important "amenity" to consider for undocumented migrants. Nonetheless, I do not find evidence in favor of that hypothesis.

[4] LAWA prohibited businesses from hiring undocumented workers and required all employers to use the "E-Verify" system in the state of Arizona.

3 Model

In this section, I present the model that I will estimate in order to analyze counterfactual policies that modify the observed risk of deportation of settled migrants across U.S. locations. The model is a simplified version of the model introduced by Kennan and Walker (2011) in a setup with international movers. In the context of the data, it is a discrete choice partial equilibrium model in which Mexican male household heads choose a final destination from a set of different locations in the U.S. and Mexico.

The main innovation of the model is that it includes the notion of deportation risk for settled undocumented migrants, which has not been previously included in previous migration models. With the presence of deportation risk, a small portion of undocumented migrants that originally chose to locate in the U.S. are sent back to Mexico and forced to relocate for at least one period.

The model that I present is closest to Lessem (2017), which is a discrete choice model where potential migrants are able to choose from multiple locations inside the U.S. However, the question that I am pursuing is different than hers. My analysis focus on the deportation risk that individuals that were successful in crossing the border face in different regions in the U.S. Instead, Lessem (2017) analyzes the effect of changes in border enforcement across border crossings and assumes that all migrants are eventually successful in crossing the border. Thus, variation in border enforcement is only reflected as variation in migration costs in her model. In my model, deportation risk does not only rise the implicit price of migration costs but also introduces heterogeneity in the distribution of preference shocks across U.S. locations.

In the specification of the model, I abstract from intertemporal considerations and focus on the decision of young male workers. However, the effect of deportation risk for settled migrants might have a considerable intertemporal component. The labor history of undocumented migrants in the U.S. might be disrupted by deportation. Considering that the labor experience and human capital accumulation in the U.S. might not be perfectly transferable to the Mexican labor markets, deportation might entail a drastic reduction in lifetime income. I will extend my model to include life-cycle considerations in a future research project.

3.1 Setup

I assume that there are two different fixed types of young male Mexican workers based on their potential legal status in the U.S. The type is identified by $Legal_i = \{0, 1\}$, where $Legal_i = 1$ if individual i would be an authorized worker in the U.S., and 0 otherwise.[5] In other words, I assume that some portion of the people that did not move to the U.S. would have become legal workers in the U.S. if they had migrated.

[5] For brevity, I will refer to the type of the individuals as L_i in what follows.

Furthermore, I assume that individuals know their own type. Apart from the legal status, there is further heterogeneity across individuals based on a vector of observables X_i. Importantly, among these observed characteristics, individuals are different depending on the community in Mexico where they come from. I index this community by j, and from now on distinguish it from the rest of the individual observables X_i.

In the model, individual i chooses destination k where he would like to work when he is 25 years old. This decision happens in year t depending on the year of birth of i. Based on the legal status of each individual i and destination k, the individual is deported and forced to relocate with probability $p_{kt}^{L_i}$. I additionally assume that if a worker in the U.S. is displaced then he is forced to choose a destination k' in Mexico, and that he does not recover the sunk migration cost of attempting to move to location k in the U.S. For all the locations in Mexico I assume that workers cannot be displaced, i.e, $p_{kt}^{L_i} = 0$, $\forall k \in Mex$, where Mex is the set of all available destinations in Mexico.

Based on this prior description, I assume that the expected utility of individual i with legal status L_i that comes originally from Mexican community j in Mexican state $s(j)$ and that attempts to settle in destination k, $U_{ikt}^{L_i}(j, X_i)$, is given by the following equation:

$$U_{ikt}^{L_i}(j, X_i) = \left(1 - p_{kt}^{L_i}\right)\left(V_{ikt}^{L_i}(j, X_i) + \varepsilon_{ikt}\right) + p_{kt}^{L_i} \max_{k' \in Mex} \{V_{ik't}^{L_i}(j, X_i) - \text{MigCosts}_{s(j)k't}^{L_i} + \varepsilon_{ik't}\} - \text{MigCosts}_{s(j)kt}^{L_i} \tag{1}$$

where the first term is the utility of choosing location k and not being subject to deportation weighted by the probability of that event. The second term is the expected utility you achieve after being deported from location k weighted by the probability of deportation, while the third term $\text{MigCosts}_{s(j)kt}^{L_i}$ represents the migration costs to reach k from state location $s(j)$, which are paid regardless of the deportation outcome.[6]

Equation (1) simplifies to the following expression when considering a location k inside of Mexico:

$$U_{ikt}^{L_i}(j, X_i) = V_{ikt}^{L_i}(j, X_i) - \text{MigCosts}_{s(j)kt}^{L_i} + \varepsilon_{ikt} \tag{2}$$

Thus, the maximization problem that the individual solves can be thought as a two-stage process. First, individual i chooses the best location in the set of Mexican locations, $k_{i,Mex}^*$, and computes the expected flow utility he would receive of settling there. Afterwards, the individual computes the flow utility of each U.S. location considering the utility he would achieve if he got deported. Finally, individual i decides which is his intended location k_i^* across both set of countries.

[6]I assume that if an individual gets deported, then he is deported back to his initial state location $s(j)$.

Individuals value each location k based on a deterministic component $V_{ikt}^{L_i}(j, X_i)$ and a set of preference shocks ε_{ikt}. Following the extensive literature on migration, I include wage differentials as a source of migration. Additionally, I include some utility components that try to capture the effect of social networks in the location of migrants. I assume that $V_{ikt}^{L_i}(j, X_i)$ is given by the following equation:

$$V_{ikt}^{L_i}(j, X_i) = \alpha \mathbb{E}\left[w_{ikt}^{L_i}(X_i)\right] + \delta_{State} \mathbb{1}(k = s(j)) + \delta_{DestUS}^{L_i} \mathbb{1}\left(k = k_{jt}^*\right) \tag{3}$$

where $\mathbb{E}\left[w_{ikt}^{L_i}(X_i)\right]$ is the expected wage of individual i with observables X_i and type L_i in location k at time t, δ_{State} is the utility gain of locating in the state $s(j)$ where your community j is located, and finally $\delta_{DestUS}^{L_i}$ is the utility gain of locating in the preferred historical location in the U.S. of i's source community, k_{jt}^*. Based on the results of the reduced-form estimation of locating in the historical location of your community presented in Appendix III, I let this utility gain vary by legal status L_i.

In terms of the random component, $\{\varepsilon_{ikt}\}$ are preference or migration cost shocks that the workers observe before attempting to locate in a destination. If the individual gets deported, he has to relocate in a destination in Mexico. I assume that the individual does not get another draw of preference or migration costs shocks after deportation.

Considering the formulation above, the intended location chosen by each individual i, k_i^*, is given by the following expression:

$$k_i^* = \arg\max_k \left[U_{ikt}^{L_{it}}(j, X_{it})\right] \tag{4}$$

Notice that the intended location k_i^* might be different than the actual final destination d_i^*. If individuals are deported in the U.S, they are forced to solve the following maximization problem in the second stage:

$$\tilde{k}_i^* = \arg\max_{k' \in Mex} \left[U_{ik't}^{L_{it}}(j, X_{it})\right] \tag{5}$$

Thus,

$$d_i^* = \begin{cases} k_i^*, & \text{if } k_i^* \in Mex, \text{ or } k_i^* \in US \text{ and not deported} \\ \tilde{k}_i^*, & \text{if } k_i^* \in US \text{ and deported} \end{cases} \tag{6}$$

4 Data

4.1 Mexican Migration Project

The main source for my estimation is the Mexican Migration Project (MMP), which has surveyed Mexican communities since 1982. For more than 20 years the MMP has gathered information related to the history of jobs and trips to the U.S. of Mexican individuals that have eventually returned to Mexico. To my knowledge, it is the most extensive survey about Mexican migration patterns. The main two advantage of the MMP over other Mexican and U.S. datasets are that the MMP has data on the legal status of migrants, and that it has a sizeable number of international migrants across a big period of time.[7]

In total, the MMP has gathered information about 23,417 male household heads interviewed mostly in Mexican communities for the period 1982-2016. Out of these number, 8,152 households heads (34.8%) have had experience in the U.S. The MMP contains an event-history file for each household head from the year of birth until the survey year. This will be my main source of information.

4.1.1 Sample selection

Due to the fact that I am focusing on a static model of migration, I have to restrict my sample to a very homogeneous group of individuals. I have decided to abstract from the problem of tied movers and married couples in international migration, so I focus on male household heads in the MMP only. Additionally, there might be learning and experience components in the decision to migrate which I would like to minimize in this first specification. Thus, I focus only on the location decision of individuals when they are 25 years old.

Using the labor-history file of each household head, I select the observations where individuals are 25 years old. Due to the retrospective way that the MMP is collected, I observe different individuals i at this particular age from the same community j in different points in time t. I consider only the observations from the sixteen-year period 1998-2013, due to data limitations on the deportation risk which I explain in the next subsection. After doing this, I end up with a total of 2,292 observations from a subset of 100 different communities. I get rid of individuals born in the U.S. (3 individuals), individuals with an unspecified location or outside of Mexico and the U.S. (19 individuals), and individuals with missing values in education attainment and legal status (8 observations). I end up with a final sample of 2,262 observations.

In Table 1, I present relevant descriptive statistics of this subsample. With respect to educational attainment,

[7]The MMP has been used extensively to analyze the determinants of the inflow and outflow of Mexican migrants to the U.S. Recent relevant examples of articles that use the MMP as the main source of information are Lessem (2017) and Thom (2010).

I classify individuals in three different categories. If individuals have 0-6 years of schooling (primary school in Mexico), then $Educ_i = 1$. $Educ_i = 2$ if the individual completed 7-9 years of education (secondary school in Mexico), and $Educ_i = 3$ if the individual has more than 9 years of education. Notice that this classification is very different than the usual categorization between high-skilled and low-skilled workers used in papers about the U.S. workforce. Finally, as initial location, I use the state of birth of individual i.

4.1.2 Construction of historically most preferred location

To construct the most preferred location of each community j at time t, I use the history of all male household heads surveyed in community j. Then, for year t, I compute the number of migrants from j that were located in each division of the U.S. in the period from $t-10$ up to $t-1$. The location k in the U.S. that has the highest number of weighted individuals for that period of time is what I define to be the most preferred location of source community j at time t, k^*_{jt}.[8]

Notice that this variable might have measurement error. Due to the retrospective nature of the MMP, individuals that were not originally from community k but that eventually moved to community j after their U.S. migration are considered in the computation of the preferred location. The MMP data does not provide information about the original community for individuals that eventually moved to community j and I am imputing k^*_{jt} for them.[9]

4.1.3 Limitations of the dataset

The most important limitation of the MMP is that it is not representative of all migrants that leave Mexico to go to the U.S. First, the surveys are mostly conducted in Mexican communities and are retrospective in nature.[10] Thus, the MMP sample does not include permanent migrants that stayed in the U.S. Second, specific communities were selected based on their past history of high migratory rates. Thus, my sample is not representative of Mexico as a whole. However, Massey and Zenteno (2000) presents evidence that the MMP sample yields a relatively accurate and valid profile of Mexican migrants to the U.S. by contrasting it with Mexican surveys that are nationally representative. Nonetheless, I avoid making any claim about the external validity of my results.[11]

[8] I could use other definitions of enclaves. For example, Edin et al. (2003) defines an "enclave" as a municipality where the size of the ethnic group relative to the municipal population was at least twice as large as the share of the ethnic group in the entire population.

[9] Nonetheless, only 146 individuals were surveyed in communities located in different states from their reported state of birth and only 32 out of these 146 individuals were international migrants, so this measurement error may be small.

[10] Only 61 out of the 2,262 male household heads were surveyed in the U.S.

[11] One could also build weights to obtain representative estimates of the Mexican population as a whole. This approach is used by Thom (2010).

A minor limitation of the dataset for this specific research question is that the MMP files do not specify which migrants got deported from the interior of the U.S. In this sense, the econometrician cannot distinguish between return migrants and deported individuals. However, this distinction is not very relevant for a one-period model where deportation risk can only act as a deterrent for international migration. Based on the MMP documentation, the labor-history of the household head for each year gives priority to U.S. locations over locations in Mexico. If individual i stayed at a U.S. location k for a non-zero amount of time during year t and the rest in Mexico (maybe because i got deported that year), then the file reports k as the location of i during that year. In this sense, the way of constructing the labor-file history allows me to observe the intended location k_i^* of every household head.[12]

4.2 Deportation statistics

In this section, I present the deportation data that I use to compute the risk of deportation that undocumented migrants face once they have been successful in crossing the border. For the analysis, I use the Survey of Migration at Mexico's Northern Border (EMIF, for its Spanish acronym).[13] The EMIF collects quarterly information about migration flows at the Mexico-U.S. border since 1993. It is currently managed by El Colegio de la Frontera Norte (COLEF), the Mexican Secretariat of Government, the National Population Council, among other government institutions. Importantly, the EMIF has a special section that interviews a representative sample of Mexican individuals that were deported by U.S. immigration officials along the border. These interviews ask not only about general individual characteristics (age, gender, level of education, state of birth), but also information about U.S. migration experience and last U.S. stay.

Table 2 presents basic summary statistics about deported migrants for the period 1998-2013 based on the EMIF surveys. One important drawback of the dataset is that it undercounts the number of deportations related to Mexican individuals that are less than 18 years old. As it is stated in the documentation of EMIF, children and teenagers are frequently sent to Mexican Consulates in the U.S. which then become responsible for their deportation. Thus, in the second and third column of Table 2 and in subsequent subsections of the paper, I restrict the EMIF sample to male individuals that are between 18 and 55 years old at the moment of deportation.

Out of all the individuals that were surveyed in the EMIF during the period, only 17.0% are women. I discard them from the analysis, because the migration patterns of women are different and more involved than those of men, as discussed by Lessem (2017). Comparing the different columns of Table 2, restricting the sample of deported individuals to men does not significantly alter the educational attainment of the

[12]The history file also includes the duration of the U.S. stay of migrant i during year t. In my restricted sub-sample of 25 year-old migrants, only 7 out of 263 migrants had a U.S. stay of less than 6 months during the year when they turned 25.

[13]Durand et al. (2001) and Gathmann (2008) are two papers that have used the EMIF for part of their analyses.

sample or the duration of the last U.S. trip in which the individual was deported.

Figure 1 shows the mean duration of the U.S. trip in which male adults got deported back to Mexico. Before 2008, the mean duration of the deported sample was less than seven months. After 2008, a bigger proportion of settled migrants were subject to deportation. In 2011, the average duration of a deported individual surveyed by the EMIF was 1,324 days (3.63 years). Figure 2 shows the proportion of deported adult male migrants by duration of stay. In 1998, 6.2% of the surveyed deported migrants had been in the U.S. for more than 1 year in their current trip. This percentage increased to more than 20% for the period 2010-2013.

The change in composition of deported migrants might be explained by two alternative causes. First, the flow of migrants attempting to cross the U.S. border has decreased drastically for the period 2000-2013. The U.S. Border Patrol reports that during 2013 there were a total of 414,397 apprehensions in the Southwest Border. In 2000, the number was almost fours times higher (1,643,679 apprehensions).[14] If less people are attempting to cross the border then that might solely explain the change in composition of deported individuals. Another explanation is that immigration policy in the U.S. has changed in the last two decades, and that now immigration authorities are increasingly targeting settled migrants.

In order to answer if the actual deportation risk for settled migrants has changed over time and across U.S. locations, I construct a measure of deportation risk that attempts to only consider the deportation risk of migrants that have been successful in crossing the border and reaching their destination in the U.S. To do this, I only consider male adults in the EMIF that reported being for two weeks or more in their last U.S. trip when they got deported. From now on, I will to refer to these migrants as "settled migrants".[15]

For migrants that stayed in the U.S. for more than a day, the EMIF has information about the U.S. state and city in which the migrant spent the biggest part of their stay. I aggregate this information for "settled migrants" and compute the number of yearly deportations based on the 10 different destinations I have defined in the U.S. in Appendix I. Afterwards, I compute an approximate number of undocumented workers in each destination using Mexican born individuals surveyed in the CPS and imputing a "potentially legal" or "potentially undocumented" type using the algorithm introduced by Borjas (2017), which is reproduced in Appendix II. Finally, I divide the total number of deportations in each location in the U.S. at year t by the estimated number of migrants at time t. I do this independently for legal and undocumented workers to obtain $p_{kt}^{L_i}$.

In practice, only 1.71% of the whole sample of deported individuals in the EMIF reported having papers to cross the border during the period 1998 - 2009. Most likely, many of these individuals travelled to the

[14] U.S. Customs and Border Protection.

[15] I chose this time period based on current U.S. Immigration law. Since 2004, migrants might be subject to expedited deportation and not allowed to have an immigration trial if they cannot prove that they have been inside the country for less than two weeks or if they are found within 100 miles of the U.S. border.

U.S. and overstayed their VISAs, so they might still be undocumented workers. Due to the small percentage of deported legal workers, I simplify the analysis and impute that the risk of deportation for legal workers located in the U.S. is zero, that is, $p^1_{kt} = 0, \forall k \in US$.

The constructed measure of deportation risk for undocumented "settled migrants" at the U.S. level is presented in Figure 3. This risk is the average risk for "potentially undocumented" male Mexican migrants that are 18-55 years old. One can observe that during the period 2007-2011, there was a significant rise in the risk of deportation which is consistent with the facts presented in the Introduction. This trend is also similar to the trends observed in Figures 1 and 2. In the same graph, I include the risk of deportation for male individuals that are 18-30 years old. To calculate this risk, I divide the total number of deported individuals surveyed in the EMIF by the estimated number of undocumented migrants in the U.S. that are in this age range. One can observe that the risk is higher than the average risk and that the spike in the period 2007-2011 was even more pronounced for individuals in this age range. In Figure 4, I present the deportation risk for undocumented males in the age range 18-30 years old in the ten different U.S. destinations that I have defined in Appendix I for the period 1998-2013. One can observe that there is variation in the deportation risk not only across years, but also across locations in a particular period of time. Additionally, from the joint analysis of Figures 3 and 4, one can conclude that the national spike in deportation risk was driven by the state of Arizona (whose local deportation risk is measured in the secondary axis of Figure 4).

Finally, one has to consider that this estimation is very likely subject to measurement error. It is likely that undocumented workers are under-counted in the CPS. Additionally, this under-counting might be more severe at times when the deportation risk is higher, so my constructed measures might be overestimated in periods where immigration enforcement increased. This problem is likely more severe at the state or division level, where under-counting might be larger in states that have more restrictive immigration policies.[16]

However, this might not be such an important problem as originally thought. Recent working papers have exploited recent Mexican administrative data about the number of *matrículas consulares* issued by Mexican Consulates to have more precise information about the size of the undocumented Mexican population in the U.S.[17] A working paper by Caballero et al. (2017) shows that there is strong agreement between the American Community Survey and the *Matrícula Consular de Alta Seguridad* dataset regarding the distribution of Mexicans across U.S. destination states for the period 2006-2010. Thus, differences in levels of under-counting at the state level might not be substantial for the CPS as well.

[16] Bohn et al. (2014) also uses CPS data to estimate the effect of Arizona's LAWA. In order to proxy for undocumented migrants, the authors focus on prime-working-age non-citizen Hispanics with low educational attainment. Using the MMP dataset allows me to clearly identify the legal status of all Mexican migrants.

[17] A *matrícula consular* is an identity card issued by the Mexican government which allows Mexican migrants to have a form of identification in the U.S. Although there is a selection issue of who has a *matricula consular*, the sample population would be biased towards undocumented migrants.

5 Estimation

5.1 Preference shocks

The sets of preference shocks ε_{ikt} is unobserved by the econometrician. For simplicity, I assume that the shocks follow the same Type I Extreme Value distribution, with the same mean and variance across destinations. I normalize the utility equation in (1) such that the mean and the variance of the preference shocks are equal to zero and one, respectively.

5.2 Legal status

The first source of individual heterogeneity is the potential legal status of i, L_i. I only observe the legal status of the individuals that actually migrated to the U.S. From my baseline dataset, 17.9% of all U.S. migrants are legal.

I use two different approaches to control for the differences in expected wages, migration costs, and utility components based on the individual legal type. In a first approach, I assign a constant probability $p_{Legal} = \mathbb{P}(L_i = 1)$ to the event that an individual is a potential legal worker in the U.S. I use the observed proportion of legal migrants to identify this parameter.

In my baseline specification, I control for individual characteristics in the MMP that might be correlated with legal status. In Table 3, I present the results of a linear probability model and a probit model, where I regress the legal type of the 263 migrants in the MMP subsample on individual characteristics. From Table 3, the level of educational attainment ($Educ_i$) and the presence of one or both parents with prior U.S. experience at time t ($ParentsUS_i$) seem to be associated with a higher probability of a migrant being legal. Thus, I include these two variables in the vector of observable characteristics X_i and assume that $\mathbb{P}\left(Legal_i = 1 \mid X_i\right) = \Phi\left(\eta_0 + \eta_1 \mathbb{1}\left(ParentsUS_i = 1\right) + \eta_2 \mathbb{1}\left(Educ_i = 2\right) + \eta_3 \mathbb{1}\left(Educ_i = 3\right)\right)$, where $\Phi\left(\cdot\right)$ is the standard normal cdf. I jointly estimate the vector η with the rest of the model parameters. However, the limitation of this approach is to assume that the unobservable characteristics of migrants are similar to those of people that do not migrate, which might be a strong assumption and end up biasing the results.

5.3 Wage specification

The MMP dataset does not have a complete history of wages for all household heads. In particular, information about wages when individuals are located in Mexico is scarce. Thus, I do not include observed wages as part of my estimation. However, I assume that individuals consider the expected wage differentials across locations to choose their intended destination.

In order to compute the expected wage differentials across locations in the U.S., I compute location-legal status-year fixed effects for the 10 U.S. divisions I have defined in Appendix I. I also estimate the returns of schooling for Mexican workers from this regression. For this, I use IPUMS-CPS data to estimate Mincer-like wage regressions of Mexican individuals that work in the U.S for the period 1998-2013.[18] In my wage regression specification, I consider male individuals that declared to be born in Mexico, reported positive wage income during the year, and had between 18-55 years old at the time of the survey. Every year, I drop the 2% highest and lowest annual wage income observations. In Table 4, I present the number of observations by location in the sample.

I run the following regression to estimate the location-legal status-year fixed effects and returns to schooling of Mexican workers in the U.S.:

$$w_{ikt} = \delta_1 Age_i + \delta_2 Age_i^2 + \sum_k \delta_k^{Years} \mathbb{1}\left(Years_i = k\right) + \sum_j \delta_j^{Educ} \mathbb{1}\left(Educ_i = j\right) + \gamma_{kt}^{L_i} + \epsilon_{ikt}$$

where w_{ikt} is the annual wage income in 1999 USD of migrant i in location k in the U.S. at time t, $Educ_i$ is the educational attainment of i, and L_i is the "most-likely" legal type assigned by the algorithm of Borjas (2017) applied to the subsample of Mexican individuals in the CPS.[19] In the regression, I also include controls for age and age squared, and three different bins depending on the number of years that have passed since person i migrated to the U.S. and t, $Years_i$. My base group are individuals with less than 6 years of education who arrived in the U.S. less than 5 years ago.[20]

The results from the regression are in Table 5. There is not substantial variation in the returns to 9 more years of education depending on the years of the CPS considered, as can be seen in columns (2)-(5). There is slightly more variation in the returns to 6-8 years of education. In my estimation, I assume that the returns to education are constant throughout the period 1998-2013.

With the estimates of $\gamma_{kt}^{L_i}$ and δ_j^{Educ}, I compute the expected annual wages of the individuals of the MMP sample across all U.S. destinations, based on their potential legal type and years of education. For all the individuals, I assume that $Age_i = 25$ and $Years_i < 5$ (omitted group in terms of years since migration). Finally, I convert the annual wage wage in U.S. dollars to 1999 Mexican pesos using the Purchasing Power Parity (PPP) conversion factor published by the World Bank for 1999 (5.634 Mexican pesos = 1 USD).

For the case of wages in Mexico, I use the National Household Income and Expenditure Survey (ENIGH)

[18]On average, between the years 1998-2013 3.8% of total CPS respondents were born in Mexico per year.
[19]This algorithm is explained in the data section and in Appendix II.
[20]IPUMS-CPS only reports the year of immigration binned in periods of 5 years.

for the years 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, and 2014 to estimate the returns to education and the location-year fixed effects. I suppose that potential legal status does not affect wages observed in Mexico. To estimate the location-year fixed effects of odd years, I average the location-year fixed effects of the years immediately prior and after each odd year.

The Mincer specification for the annual wages in Mexico is very similar to the specification of U.S. wages, except that I do not include the effect of legal status and years since migration. I include in my sample all male individuals 18-55 years old who reported positive income and that were employed during the last six months prior to the survey. I exclude the 2% highest and lowest hourly wage observations from the sample, as I did in the CPS. The regression for wages that I run is the following:

$$w_{ikt} = \delta_1 Age_i + \delta_2 Age_i^2 + \sum_j \beta_{Educ}^j \mathbb{1}\left(Educ_i = j\right) + \gamma_{kt} + \epsilon_{ikt}$$

where w_{ikt} is i's annual wage income computed from monthly wage data and deflated to 1999 Mexican pesos, and the rest of the variables are defined in the exact same way as in the Mincer regression for U.S. wages. The results of my baseline regression are presented in Table 6. As in the case of U.S. wages, the returns to education and age do not vary over time. For the estimated wages across locations in Mexico, I again use the returns obtained in the regression with all the years of the survey and impute that $Age_i = 25$, $\forall i$.

5.4 Migration costs

In order to reduce the number of parameters to estimate, I assume simple specifications for the migration costs of international and internal moves. In the baseline model, I suppose that the migration cost of moving inside Mexico is equal to zero, while the cost of an international move only depends on the legal type of individual i, $\bar{\gamma}^{L_i}$, and is constant across time. For legal migrants, $\bar{\gamma}^1$ might represent the costs of obtaining a visa or applying for citizenship, while for undocumented workers $\bar{\gamma}^0$ includes the costs of crossing the border.

I present results where I vary the specification of the unobserved migration costs. In an alternative specification, I include the notion that the migration cost associated with moving from location j to destination k increases with the distance between these two locations. Thus, I include the term $\gamma^{km} \times \text{Distance}\left(s(j), k\right)$ in $\text{MigCosts}_{s(j)kt}^{L_i}$, where $\text{Distance}\left(s(j), k\right)$ is the distance (measured in thousand of kilometers) between the original state location j and the intended location k. γ^{km} represents then the average cost of migrating 1,000 kilometers. I consider the same term for both internal and international movements.[21]

I also let the international migration costs vary by the level of educational attainment, as in Lessem (2017).

[21] Since I have included already the benefit of staying in your home state in the utility function and I have only one time period, I am normalizing to zero the fixed cost of moving inside of Mexico in this alternative specification.

The parameters γ^{Educ_2} represents the difference in migration costs of individuals that have 6-9 years of education with respect to the migration costs of individuals with less than 6 years of education. γ^{Educ_3} has an analogous interpretation. In terms of another observable characteristic that might be correlated with migration costs, I also analyze the possibility that having a parent with prior U.S. experience mitigates migration costs. I extend the migration specification with the parameter γ^{Parent} to allow for that option.

Finally, one important restriction of the migration costs of the baseline model is that the fixed migration cost of undocumented migrants is assumed to be fixed throughout the period 1998-2013. Even though the most important federal immigration reforms were prior to this period of time, the degree of border enforcement increased substantially during that period. In an alternative specification, I allow the migrations costs of undocumented migrants to vary with the total budget of the U.S. Customs and Border Protection Agency, $Budget_t$. I include the term $\gamma^{Budget} \times log(Budget_t)$ to allow for this possibility.[22]

5.5 Deportation risk and beliefs

In the specification of the flow utility, I have assumed that individuals are risk neutral.[23] In terms of the beliefs about deportation risk, I assume that they have perfect foresight. In this sense, they observe $p_{kt}^{L_i}$ with precision, $\forall k$ in year t. In terms of imputation, I use the estimated deportation risk at division k at time t for male migrants in the age range of 18-30 years old.

5.6 Likelihood function

In the first draft of this paper, I used Maximum Likelihood to estimate the model. However, there was one important mistake in the computation of the likelihood for undocumented immigrants. Even though the maximization problem of the individual seems simple, the appropriate likelihood for undocumented migrants does not have a nice closed-form solution.

To provide some intuition about the complexity in the likelihood function for undocumented migrants, I refer back to equation (1) that provided the flow utility of each location k in the set of destinations. I drop the subscripts i and t for clarity. For simplicity, assume that the best location in Mexico for individual i, k^*_{Mex}, is known *ex-ante* and that the flow utility derived from that location is $U_{k^*_{Mex}}$.

Individual i has now to determine which is the best location in the U.S, k^*_{US}, conditional on the fact that the best location in Mexico is k^*_{Mex}. In equations, k^*_{US} has to satisfy the following set of conditions in order

[22] I do not instrument the level of budget of border patrol enforcement in time t with past levels of enforcement.

[23] Additional individual heterogeneity based on risk aversion might be very interesting to analyze in the context of migration and deportation risk.

to be the optimal choice in the set of all U.S. locations (represented by the set US):

$$U_{k^*_{US}} \geq U_k,\, \forall k \in US \iff U_{k^*_{US}} \geq \max_{k \neq k^*_{US} \in US} U_k \tag{7}$$

Using equation (1), one can group all the deterministic components of location k in the term δ_k. For each possible destination k in the U.S., this deterministic component includes the utility obtained in k^*_{Mex} if the individual gets deported. I additionally relabel $(1 - p_k)$ as σ_k. Rewriting equation (7) in terms of δ_k and σ_k, and using the fact that $\varepsilon_k \sim$ Type I E.V. one obtains the following modified expression for (7):

$$\underbrace{\delta_{k^*} + \sigma_{k^*}\varepsilon_{k^*}}_{GEV(\delta_{k^*},\sigma_{k^*},0)} \geq \max_{k \neq k^*} \underbrace{[\delta_k + \sigma_k \varepsilon_k]}_{GEV(\delta_k,\sigma_k,0)} \tag{8}$$

where $GEV(\delta_k, \sigma_k, 0)$ is the Generalized Extreme Value (GEV) distribution with location parameter δ_k, scale parameter σ_k, and shape equal to 0. Notice however that it is difficult to compute the probability of the event shown in equation (8), due to the fact that the distribution of random shocks is independent but not identically distributed ($i.n.i.d$) across locations. Variation in deportation risk across locations causes each location to have a different scale.[24]

Hence, one cannot obtain a closed form solution for the probability that location $k \in US$ is the best location among U.S. locations, even when one knows that the best outside option in Mexico is k^*_{Mex}. In the complete set-up where you see that individual i chooses k in the U.S. as intended location without observing which is the best second alternative in Mexico, the computation of the likelihood of that event becomes more complicated. I wasn't even able to come up for an expression of the likelihood in terms of integrals of functions of deterministic and observed components.

5.7 Estimation method

Instead, I use Simulated Method of Moments (SMM) to estimate the parameters of the migration model. This method does not rely on having an expression for the likelihood function of each location.

In terms of number of different locations in the U.S., I use the classification presented in Appendix I and consider 10 different locations based mostly on Census divisions and border states. In terms of destinations in Mexico, I consider the 32 Mexican states as different locations. Since my initial model just has one period, I do not need to reduce the number of destinations, whereas Lessem (2017) included only four different U.S. locations (Arizona, California, Texas, and rest of U.S.) and 20 locations in Mexico to reduce the number of possible states.

[24]In my first draft, I compute an incorrect likelihood function. The inaccurate estimates and bad fit were a result of this mistake.

6 Results

Table 7 presents the estimates of the parameters of my baseline model (Model II) and alternative specifications of the model obtained by SMM. For each possible guess of the parameters, I obtain moments from 100 simulated datasets generated by the model with those parameters. I use a Nelder-Mead simplex algorithm to obtain the estimated parameters that minimize the distance between the estimated simulated moments and the observed moments in the data.[25][26] In my estimation, I restrict $\bar{\gamma}^0$, $\bar{\gamma}^1$, and γ_{km} to be positive, while p_{legal} to be between 0 and 1. I computed the standard errors presented in Table 7 with 100 bootstrap iterations of the SMM procedure.[27]

Column (II) presents my baseline estimation in which international migration costs are fixed across time and solely determined by legal status. Also, the probability of being a legal worker in the U.S. depends on the level of education and having at least one parent wit prior U.S. experience (η parameters). In contrast, Column (I) presents the alternative model where the probability of being legal is independent of all the observable individual characteristics and equal to p_{Legal}. The estimated value for $p_{Legal} = 0.243$. This means that Model I estimates that 24.3% of all Mexican male households surveyed in the MMP would be legal workers in the U.S. if they decided to migrate. Notice finally that the main difference between the estimates of these two alternative specifications are the migration costs for undocumented migrants.

Column (III) instead considers that the level of educational attainment modifies the cost of migration but that it does not alter the probability of acquiring potential legal status in the U.S. Column (IV) includes distance as a determinant in internal and international migration. Column (V) expands on (IV) and includes the budget of the U.S. Customs and Border Protection agency. In order to secure identification in specifications (IV) and (V) with additional parameters, I include additional moments to match in the SMM procedure related to the mean distance of internal and international moves, and observed correlation between border patrol budgets (in log terms) and international migration rates. Finally, the model presented in Column (VI) includes the mitigating effect on international migration costs of having a parent with prior U.S. experience.

Across all model specifications, the estimated values for α, δ_{State}, δ_{DestUS}^{Legal}, and $\delta_{DestUS}^{Illegal}$ are in general very similar to one another and are reassuring of the possibility of successful identification of the parameters. $\hat{\alpha}$

[25]The moments that I match in the baseline specification are the following: % of international migrants, % of internal movers, % of migrants that have parents with U.S. experience, % of migrants with 7-9 years of education, % of migrants with more than 9 years of education, % of legal migrants located in historical enclave, % of undocumented migrants located in historical enclave, % of legal migrants, % of migrants located in California, Herfindahl-Hirschman index of migrants' locations.

[26]I use the function "fminsearch" programmed in Matlab to compute my results. I did not use the two-step procedure to obtain efficient estimators. Instead, I used the identity matrix as my weighting matrix in all the specifications. This should not affect the consistency of my estimators.

[27]Due to time and programming constraints, I only generated 20 simulated datasets for each parameter guess inside each of the 100 bootstrap iterations.

is in the range [0.09,0.12]. In the analysis, the units of annual wages are thousands of Mexican 1999 pesos. The estimated utility gain of locating in the historical location of your source community is very similar for documented and undocumented workers. Connecting this result with Appendix III, the risk of deportation might be one of the crucial reasons why the change from undocumented to legal status is associated with moving to the historical enclave of your source community. However, one important final concern about these estimates is that the estimated fixed cost of international migration for legal workers ($\bar{\gamma}^1$) is higher than for undocumented workers ($\bar{\gamma}^0$).

6.1 Fit of the model

To assess the fit of the model, I simulate 1,000 times the location decisions of the individuals of my main sub-sample based on the estimated parameters presented in Table 7. I compare the empirical moments of the 1,000 simulations with the observed data moments. I present in Table 8 all the moments that I selected in the SMM estimation, among other moments. Additionally, I include implicit moments obtained from the simulations of the model that cannot be directly observed in the MMP data. These moments can not be calculated from the data because legal status is not observed for non-migrants.

The fit of the baseline model (column II) is relatively good. The international migration rate in the simulations (10.71%) is close to the observed one in the data (11.63%). Other moments that are related to internal migration and location decisions in the U.S. are also close to the observed patterns in the data. However, the baseline model does not do a good job of fitting the degree of selection of migrants. In particular, the estimated percentage of migrants that have more than 9 years of education is overestimated in the simulations. This is consistent with results presented in Lessem (2017) that show that migration costs increase with educational attainment. In my baseline model, migration costs are not affected by education. In column (III), I modify the specification to allow education to affect migration costs but not the probability of acquiring legal status. This worsens the overall fit of the model.

One of the few moments that cannot be fitted with the baseline model is the proportion of international migrants that have parents with U.S. experience. In the data, 14.07% of all migrants have parents with U.S. experience prior to year t, while the unconditional mean across household heads is equal to 3.9%. This moment is hard to match because the percentage of individuals with parents with prior U.S. experience is very low. In model (VI), where I include the role of having parents with U.S. experience as an explanation of lower migration costs, the fit is marginally closer to the data moment.

In the bottom panel of Table 7 I include implied moments in the different specifications that are unobserved in the MMP data. In particular, I estimate in the baseline model that around 24.16% of the MMP sample of household heads would have become legal migrants in the U.S. if they had decided to migrate. Notice that if this implied moment is lower, however, if one includes the role of distance, border patrol enforcement, and having a parent with prior U.S. experience in the determination of the migration costs.

Finally, to further assess the fit of the baseline model I present in Figure 5 the average predicted international migration rate for each year in the sample. In the estimation of the baseline model, all the parameters are time invariant and all the moments that I selected in the SMM criterion are computed across time. Thus, the predicted trend in Figure 5 is only a result of changes in wage differentials across countries, deportation risk, and observed characteristics of male household heads across years. This trend follows the data in a reasonable fashion.

7 Counterfactual experiments

In this section, I present four different counterfactual scenarios where immigration policy or economics conditions in the U.S. are changed. With the estimated baseline and alternative models, I estimate how the location decision of Mexican households would have changed under each regime.

7.1 Homogeneous deportation risk across U.S. locations

In this counterfactual experiment, I set up the deportation risk at each U.S. location to be constant to the national deportation risk observed during that year. In this sense, I quantify whether international migration moves are sensible to local changes in immigration policy or not, while holding fixed the aggregate deportation risk.[28]

The results of 1,000 simulations with the new deportation regime are presented in Table 9. As can be observed by comparing the moments presented in Table 9 with those in Table 8, under all the model specifications the changes in the international migration margin are minimal. The effects of the policy are different than zero only in specification (V), which allows the impact of border enforcement on migration costs to be positive for undocumented immigrants and that over-predicts the percentage of undocumented migrants that settle in the historical enclave of their source community.

In terms of the particular location inside of the U.S., the effects are also close to zero. In all specifications, the percentage of undocumented immigrants that settle in the historical enclave (California, in most

[28]Importantly, local wage fixed effects are hold constant. In this sense, the counterfactual experiment might not be an appropriate general equilibrium counterfactual if local wages are affected by immigration policy.

cases) increases. Finally, the effect on the concentration of immigrants across locations is minimal. However, all specifications point out to the same result. Undocumented immigrants become marginally more geographically concentrated without local variation in deportation risk.

7.2 No deportation risk

In this counterfactual immigration scenario, I estimate what would have been the migration patterns if the risk of deportation for undocumented migrants was zero throughout the period 1998-2013. The set of moments under this new counterfactual are included in Table 10. In the baseline model, the international migration rate would have increased from 10.71% to 10.86%. Thus, an additional 0.15% of the male household heads surveyed in the MMP would have migrated to the U.S. if there was no deportation risk. The effect is very small.

In terms of selection of migrants, this policy does not affect the location decision of legal migrants. Legal migrants would represent now 18.04% of total stock of migrants, instead of 18.28%. With respect to selection of individual characteristics, this policy does not affect the degree of migrants' selection on observables. The effect of deportation risk on the dispersion of migrants is also small.

7.3 Increase of deportation risk to 15%

In this counterfactual immigration scenario, I estimate what would have been the migration patterns if the risk of deportation for undocumented migrants was raised up to 15% throughout the period 1998-2013. The set of moments under this new counterfactual are included in Table 11. In the baseline model (II), the international migration rate would have decreased by 0.67 percentage points from an original rate of 10.71% (a decrease of 6.26%). A crude approximation of the elasticity of international migration rates with respect to deportation risk is equal to -0.016 (since the deportation risk is increased roughly by 400% during the time period). Across all model specifications, the range of this elasticity is [-0.01,-0.07].[29]

Under this major change in immigration policy, legal migrants end up representing 19.49% of the total stock of immigrants. Since legal immigrants are associated with higher levels of educational attainment, this policy marginally increases the degree of selection of Mexican migrants. Now, migrants with 9 more years of education represent 23.9% of the total stock of migrants (compared to 23.7% in the original set-up).

[29] Model (IV) that considers the role of the U.S. Customs and Border Protection agency provides the upper bound on this elasticity. Deportation risk becomes more relevant as migration costs increase.

7.4 Increase of 10% in U.S. wages

I also estimate the effect of a homogeneous increase of 10% in U.S. wages across the period 1998-2013. Compared to changes in immigration policy that only (marginally) affect the decision of undocumented migrants, this counterfactual affects the decision of all potential Mexican migrants. As such, the effect of wages on migration rates is substantially more important than immigration policy.

In my baseline model, the elasticity of international migration rates with respect to U.S. wages is equal to 1.18. In the baseline model, the counter factual policy increases international migration rates from 10.71% to 12.15%, representing an 11.84% increase in the international migration rate. Across all specifications, the range of this elasticity is [0.8, 1.5]. Lessem (2017) estimates that this elasticity is equal to 1.17. Hanson and Spilimbergo (1999) estimates this range to be [0.9, 1.64].[30] This provides further evidence that my estimates seem plausible.

7.5 International migration rate by year

The international migration rate by year under each one of the four counterfactual policies using the baseline model is presented in Figure 6. In the figure, I have omitted the counterfactual where the deportation risk is homogeneous across locations and set up to the observed national level because the migration pattern is identical to the trend in the baseline model. The main result is evident from the graph. The international migration decision is more sensitive to economic fluctuations in wages than to changes in immigration policy.

8 Conclusion

In this paper, I develop a static model that allows me to study the effect of deportation risk on the location decisions of legal and undocumented Mexican workers in the U.S. I focus on the location decision of young male household heads when they turn 25 years old. In their utility maximization problem, undocumented individuals need to consider that with a small chance they are subject to deportation in the U.S. depending on where they are located.

I find that throughout the time period 1998-2013 in which U.S. immigration policy shifted and deportation risk for "settled migrants" increased in the U.S., young male household heads surveyed in the MMP were not very sensitive to deportation risk. In my estimation, I find that the elasticity of the international migration rate with respect to the deportation probability is roughly more than 10 times smaller in absolute terms

[30] However, my results are not directly comparable. I am analyzing a particular sub-sample of young men in a static set-up.

than the elasticity of the international migration rate with respect to U.S. wages. This is consistent with the scarce literature that has concluded that the impact of local immigration policy on international migration patterns is small.

Additionally, I find that deportation risk had a minimal effect on the dispersion of undocumented and documented migrants surveyed in the MMP. I do not find evidence that deportation risk spurs movement across census divisions. These results are inconsistent with findings in Watson (2013). This might be due to the fact that Watson (2013) uses data at a more disaggregate level. Another explanation for the difference in findings is that I focus on a specific group that has just entered the labor market, which might be less susceptible to the intertemporal losses associated with deportation and that depend more on the networks present in the historical enclave of their source community.

A natural extension of the model would be to analyze the effects of deportation risk in a dynamic life-cycle model. All the results about selection of immigrants might change with a dynamic scope. Migrants that have "life cycle" motivations might be less susceptible to move to the U.S. or have less incentives to invest in specific U.S. human capital if there is a higher chance of deportation. Thus, deportation risk might worsen the initial selection and posterior assimilation of Mexican migrants. One of my potential future research questions will be focused on this particular topic.

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Figure 1: Mean duration of stay during last trip in U.S. before deportation, 1998-2013

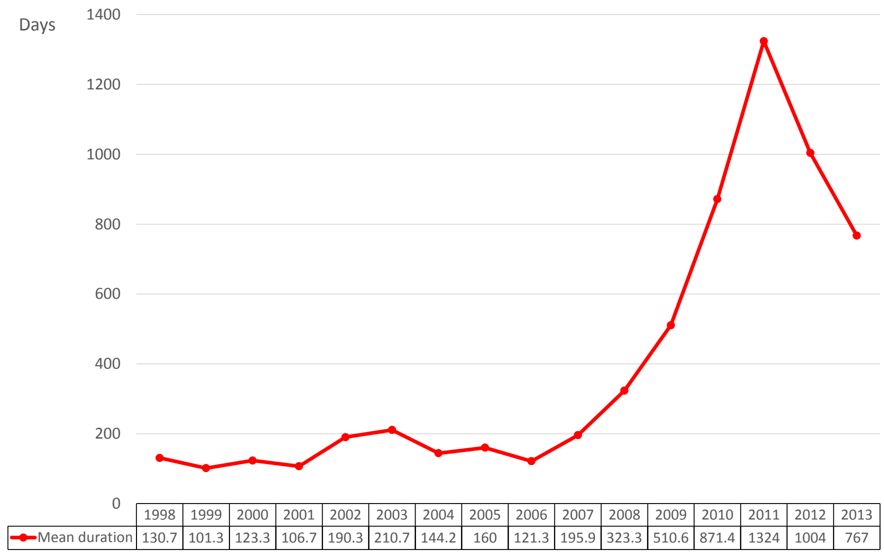
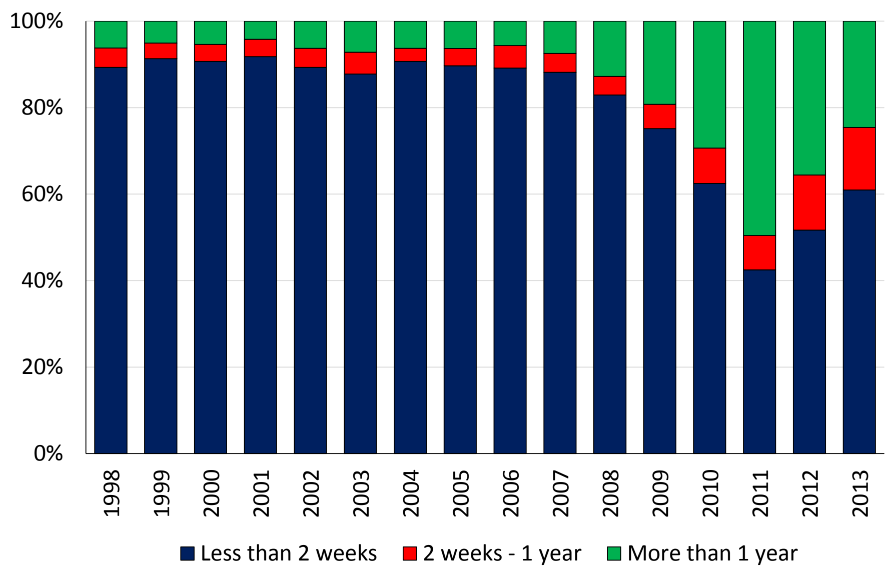


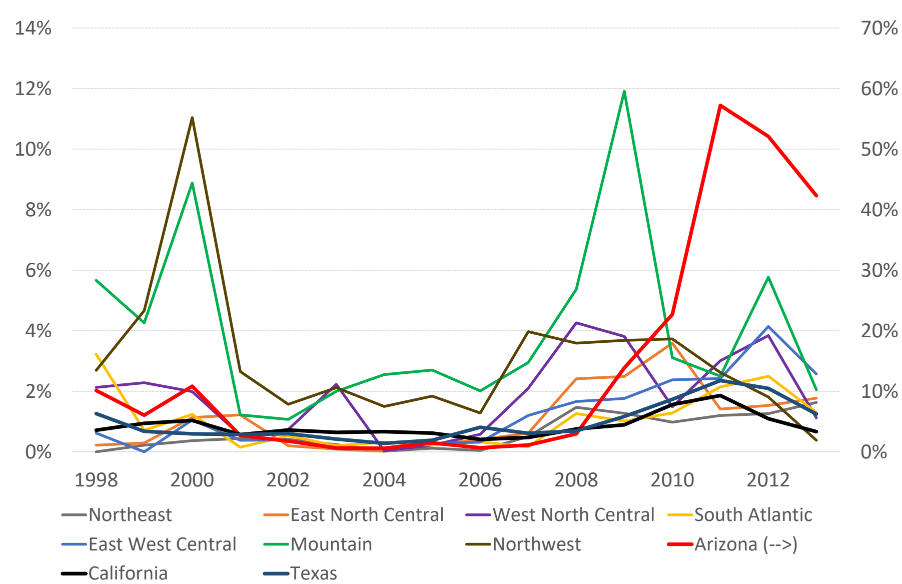
Figure 2: Classification of deported individuals by length of last trip in U.S., 1998-2013



Source: EMIF Norte.

Figure 3: Constructed measure of deportation risk for "settled migrants" at the U.S. level, 1998-2013

Figure 4: Constructed measure of deportation risk for adult "settled migrants" in selected U.S. locations, 1998-2013



Source: EMIF Norte and CPS.

Figure 5: Model fit.- International migration rates by year in baseline model, 1998-2013

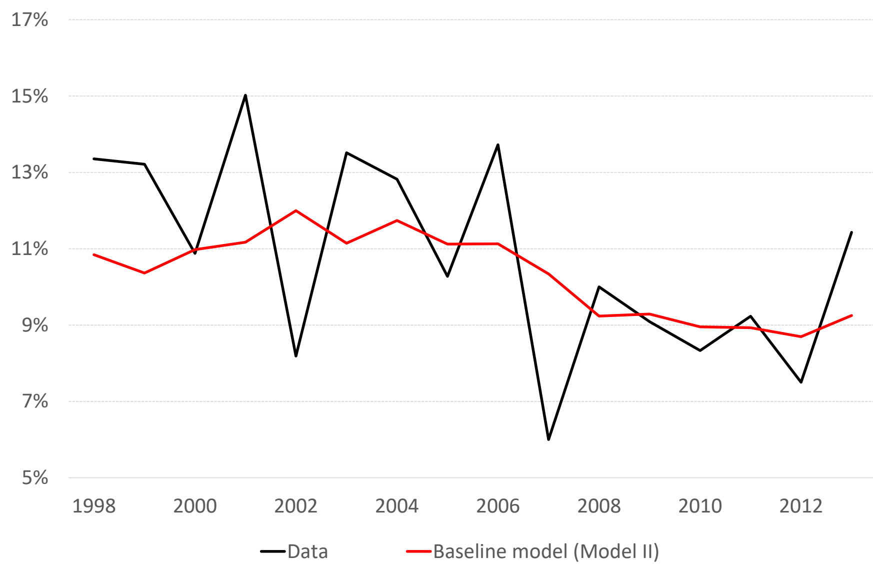


Figure 6: Counterfactuals.- International migration rates by year under counterfactual migration policies, 1998-2013

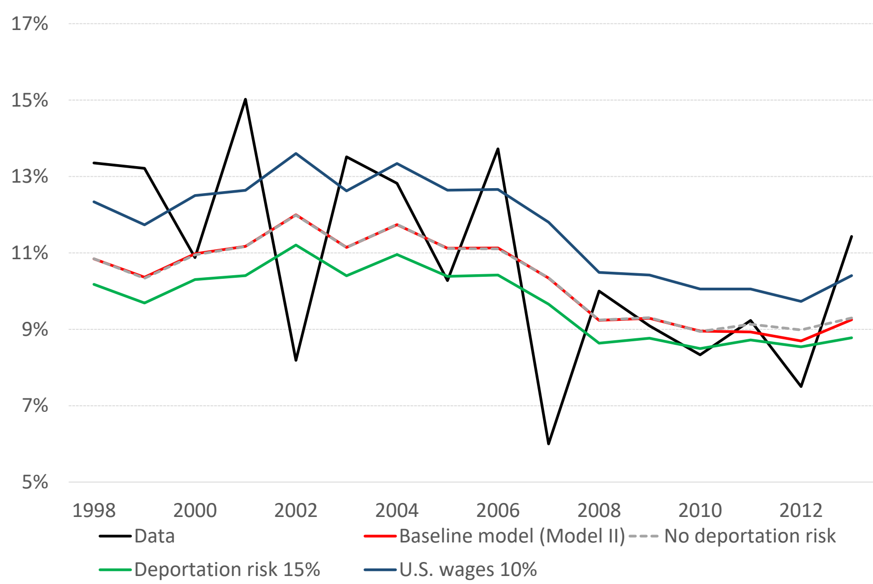


Table 1: Descriptive statistics of MMP selected subsample

	All sample	Migrants	Non-migrants
Educational attainment:			
Educ: 0 - 6 yrs. of education	35.4%	40.7%	34.7%
Educ: 7 - 9 yrs. of education	38.0%	42.6%	37.4%
Educ: $>$ 9 yrs. of education	26.6%	16.7%	27.9%
Parents with U.S. experience	3.9%	14.1%	2.6%
Siblings with U.S. experience	19.1%	42.6%	16.0%
Historical enclave:			
California	55.8%	43.7%	57.4%
Division V: South Atlantic	12.0%	13.7%	11.8%
Division I & II: Northeast	8.7%	17.1%	7.6%
Division III: East North Central	6.2%	9.9%	5.7%
Texas	8.0%	8.0%	8.1%
In Rest of U.S.	8.5%	7.6%	8.5%
No Enclave	0.8%	0.0%	0.9%
Number of observations	2,262	263	1,999

Subsample: Migrants in the U.S.

	All	Legal	Undocumented
Location in U.S.:			
California	32.3%	29.8%	32.9%
Division V: South Atlantic	17.5%	19.1 %	17.1%
Division I & II: Northeast	16.0%	12.8%	16.7 %
Division III: East North Central	11.8%	4.3%	13.4 %
Texas	8.0%	14.9%	6.5%
In Rest of U.S.	14.4%	19.1 %	13.4 %
Location in historical enclave	60.1%	70.2%	57.9%
Educational attainment:			
Educ: 0 - 6 yrs. of education	40.7%	21.3%	44.9%
Educ: 7 - 9 yrs. of education	42.6%	48.9%	41.2%
Number of observations	263	47	216

Table 2: Descriptive statistics of EMIF sample, 1998-2013

Variables	All sample	Sub-sample of males, 18-55 yrs. old All sub-sample	Stay > 2 weeks
Male	83.0%	-	-
Age	27.92	28.56	31.28
Education			
Educ: 0 - 5 yrs. of education	40.6%	41.2%	37.6%
Educ: 6 - 9 yrs. of education	43.0%	42.7%	40.4%
Educ: More than 9 yrs. of education	16.4%	16.1%	22.1%
Duration last U.S. trip			
Less than 1 day	45.9%	44.0%	-
1 day - 2 weeks	34.5%	34.1%	-
2 weeks - 3 months	3.4%	3.6%	16.4%
3 months - 1 year	2.5%	2.7%	12.3%
1 year - 2 years	1.4%	1.6%	7.3%
More than 2 years	12.3%	14.0%	63.9%
No. observations	108,864	84,949	18,634

Table 3: Regression of legal type on individual characteristics

	(1)	(2)
Dep. Variable: Legal (indicator function)	LPM	Probit
Educ: $6-9$ yrs. of education	0.0956**	0.4379**
	(0.0472)	(0.2188)
Educ: More than 9 yrs. of education	0.1789**	0.6984***
	(0.0763)	(0.2677)
Parents with U.S. experience	0.1834**	0.5761**
	(0.0835)	(0.2410)
Siblings with U.S. experience	0.0235	0.0753
	(0.0458)	(0.1886)
Constant	0.0722**	-1.3982***
	(0.0341)	(0.1913)
Observations	263	263
R-squared / pseudo R-squared	0.0734	0.0722

Robust standard errors in parentheses

*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 4: Distribution of Mexican individuals in CPS data included in Mincer wage regressions

Destination U.S.	No. Observations	% of total sample
Division I & II: Northeast	2,511	3.88%
Division III: East North Central	5,692	8.79%
Division IV: West North Central	3,374	5.21%
Division V: South Atlantic	5,875	9.08%
Division VI & VII: East and West South Central	1,331	2.06%
Division VIII: Mountain	6,671	10.31%
Division IX (mod): Northwest	3,352	5.18%
Arizona	2,612	4.04%
California	21,802	33.69%
Texas	11,503	17.77%
Total	64,723	100.00%

Table 5: Mincer wage regressions, U.S.

Dep. Var: Annual wage income (1999 USD)	(1) All	(2) 1998-2001	(3) 2002-2005	(4) 2006-2009	(5) 2010-2013
Age	1,152***	1,210***	1,104***	1,191***	1,164***
	(31.71)	(66.05)	(62.25)	(61.48)	(65.91)
Age^2	-13.85***	-15.12***	-13.39***	-14.32***	-13.57***
	(0.443)	(0.940)	(0.889)	(0.855)	(0.893)
Years since migration: 5 - 9	307.1**	483.7*	1,001***	65.35	-1,193***
	(126.0)	(247.7)	(227.1)	(238.2)	(339.8)
Years since migration: 10 - 19	1,244***	2,031***	1,681***	1,448***	-950.4***
	(123.3)	(241.7)	(216.4)	(244.2)	(320.9)
Years since migration: 20 or more	3,617***	4,359***	4,051***	3,843***	1,485***
	(156.3)	(341.6)	(292.7)	(301.9)	(360.4)
Educ: 6 - 9 years of education	763.7***	1,239***	542.4**	836.7***	480.7**
	(111.0)	(229.6)	(212.8)	(220.3)	(226.6)
Educ: $>$ 9 years of education	3,750***	3,754***	3,423***	4,013***	3,727***
	(96.85)	(200.4)	(186.0)	(191.6)	(197.9)
Observations	64,723	13,454	16,535	17,917	16,817
R-squared	0.109	0.124	0.105	0.113	0.099

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Mincer wage regressions, Mexico

Dep. var.: Annual wage income (1999 Pesos)	(1) All[31]	(2) 1998, 2000	(3) 2002, 2004	(4) 2006, 2008	(5) 2010, 2012
Age	3,226***	3,155***	3,125***	3,457***	2,929***
	(48.97)	(125.2)	(88.98)	(100.3)	(102.0)
Age^2	-35.73***	-35.96***	-35.73***	-37.11***	-32.25***
	(0.70)	(1.79)	(1.27)	(1.45)	(1.46)
Educ: 6 - 9 years of education	10,282***	10,557***	9,661***	10,972***	9,968***
	(150.3)	(415.8)	(279.3)	(300.5)	(310.3)
Educ: More than 9 years of education	28,805***	30,013***	27,131***	31,174***	27,688***
	(199.1)	(602.5)	(384.6)	(388.3)	(399.9)
Observations	121,022	15,879	29,307	35,594	27,196
R-squared	0.272	0.284	0.284	0.266	0.247

Robust standard errors in parentheses

***p< 0.01, **p< 0.05, *p< 0.1

[31] This column includes observations for the year 2014, which are used to compute the location fixed effects for the year 2013.

Table 7: Estimates of the parameters based on different model specifications

	(I)	(II)	(III)	(IV)	(V)	(VI)
α	0.097	0.104	0.114	0.105	0.093	0.115
	(0.014)	(0.020)	(0.019)	(0.027)	(0.019)	(0.016)
δ_{State}	3.146	3.187	3.305	2.313	2.724	2.698
	(0.325)	(0.324)	(0.276)	(0.397)	(0.415)	(0.198)
δ_{DestUS}^{Legal}	1.100	1.105	1.162	1.029	0.937	1.149
	(0.121)	(0.174)	(0.349)	(0.388)	(0.436)	(0.168)
$\delta_{DestUS}^{Illegal}$	1.047	0.997	1.021	0.997	2.527	0.906
	(0.068)	(0.073)	(0.080)	(0.276)	(0.607)	(0.093)
$\bar{\gamma}^1$	0.657	0.602	0.578	0.581	0.568	0.528
	(0.049)	(0.057)	(0.080)	(0.083)	(0.061)	(0.070)
$\bar{\gamma}^0$	0.098	0.304	0.282	0.161	0.203	0.183
	(0.059)	(0.090)	(0.082)	(0.093)	(0.046)	(0.144)
γ^{Km}	-	-	-	0.066	0.106	-
				(0.022)	(0.030)	
γ^{Budget}	-	-	-	-	0.082	-
					(0.019)	
γ^{Educ_2}	-	-	0.998	-	-	-
			(0.001)			
γ^{Educ3}	-	-	1.004	-	-	-
			(0.002)			
$\gamma^{Parents}$	-	-	-	-	-	-0.969
						(0.233)
p_{Legal}	0.243	-	-	-	-	-
	(0.028)					
η_0	-	-1.222	-0.815	-1.332	-1.627	-1.971
		(0.220)	(0.298)	(0.287)	(0.270)	(0.192)
η_1	-	0.737	0.768	0.584	0.597	0.688
		(0.154)	(0.155)	(0.126)	(0.135)	(0.158)
η_2	-	0.562	-	0.621	0.426	0.368
		(0.093)		(0.109)	(0.093)	(0.128)
η_3	-	0.862	-	0.683	0.616	0.733
		(0.163)		(0.161)	(0.131)	(0.201)

Table 8: Moments in the data vs. simulated moments

Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
International migrants	11.63%	14.13%	10.71%	4.93%	19.78%	11.30%	11.66%
Internal migrants	6.15%	7.60%	8.67%	10.79%	18.04%	15.11%	15.74%
Not movers	82.23%	78.27%	80.62%	84.28%	62.18%	73.59%	72.60%
As proportion of international migrants:							
With parents with US experience	14.07%	3.81%	3.52%	2.78%	3.41%	3.50%	4.03%
Educ: 0-6 yrs. of education	40.68%	37.95%	39.85%	88.44%	40.43%	39.02%	39.03%
Educ: 7-9 yrs. of education	42.59%	37.05%	36.46%	7.06%	35.89%	37.12%	36.27%
Educ: >9 yrs. of education	16.73%	25.01%	23.69%	4.50%	23.67%	23.86%	24.70%
Located in enclave	60.08%	58.51%	59.92%	61.91%	57.90%	98.49%	57.45%
Located in California	32.32%	33.70%	34.23%	35.09%	34.62%	55.87%	32.27%
Legal	17.87%	12.18%	18.28%	17.72%	11.27%	4.89%	8.91%
HHI of locations	0.1858	0.1694	0.1736	0.1828	0.1723	0.3494	0.1634
% Legal migrants in enclave	70.21%	72.07%	69.57%	71.71%	69.33%	70.73%	67.18%
% Undocumented migrants in enclave	57.87%	56.64%	57.77%	59.80%	56.45%	99.93%	56.49%
Mean length - international trip	2.44	2.37	2.37	2.38	2.31	2.34	2.36
Mean length - internal trip	0.48	0.77	0.77	0.77	0.70	0.67	0.78
Correlation mig. rate and budget	-0.59	-0.23	-0.26	-0.40	-0.41	-0.44	-0.37

Implied Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
Prop. legal type in MMP	N.A.	24.23%	24.16%	21.78%	19.90%	10.93%	6.37%
As proportion of MMP population with legal type:							
U.S. migrants	N.A.	7.10%	8.10%	4.01%	11.20%	5.05%	16.32%
Internal migrants	N.A.	11.25%	10.18%	11.24%	23.45%	17.95%	13.41%
Non-movers	N.A.	81.65%	81.72%	84.75%	65.35%	77.00%	70.28%
As proportion of MMP population with not legal type:							
U.S. migrants	N.A.	16.37%	11.54%	5.19%	21.91%	12.07%	11.35%
Internal migrants	N.A.	6.44%	8.18%	10.67%	16.70%	14.76%	15.90%
Non-movers	N.A.	77.19%	80.27%	84.14%	61.39%	73.17%	72.76%

Table 9: Counterfactual I: Constant deportation risk across locations

Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
International migrants	11.63%	14.13%	10.72%	4.93%	19.78%	11.37%	11.65%
Internal migrants	6.15%	7.60%	8.67%	10.79%	18.04%	15.07%	15.75%
Not movers	82.23%	78.27%	80.62%	84.28%	62.18%	73.56%	72.61%
With parents with US experience	14.07%	3.81%	3.51%	2.76%	3.40%	3.42%	4.02%
Educ: 0-6 yrs. of education	40.68%	37.95%	39.83%	88.45%	40.41%	38.97%	39.04%
Educ: 7-9 yrs. of education	42.59%	37.03%	36.46%	7.06%	35.89%	37.04%	36.23%
Educ: >9 yrs. of education	16.73%	25.01%	23.71%	4.49%	23.71%	23.98%	24.72%
Located in enclave	60.08%	58.60%	60.12%	62.11%	58.07%	98.51%	57.78%
Located in California	32.32%	33.81%	34.46%	35.50%	34.88%	56.82%	32.70%
Legal	17.87%	12.18%	18.27%	17.71%	11.27%	4.86%	8.92%
HHI of locations	0.1858	0.1698	0.1745	0.1845	0.1735	0.3577	0.1648
% Legal migrants in enclave	70.21%	72.07%	69.57%	71.71%	69.33%	70.73%	67.18%
% Undocumented migrants in enclave	57.87%	56.74%	58.02%	60.05%	56.65%	99.94%	56.85%
Mean length - international trip	2.44	2.37	2.37	2.38	2.31	2.34	2.36
Mean length - internal trip	0.48	0.77	0.77	0.77	0.70	0.67	0.78
Correlation mig. rate and budget	-0.59	-0.23	-0.25	-0.39	-0.38	-0.39	-0.35

Implied Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
Prop. legal type in MMP	N.A.	24.23%	24.16%	21.78%	19.90%	10.93%	6.37%
As proportion of MMP population with legal type:							
U.S. migrants	N.A.	7.10%	8.10%	4.01%	11.20%	5.05%	16.32%
Internal migrants	N.A.	11.25%	10.18%	11.24%	23.45%	17.95%	13.41%
Non-movers	N.A.	81.65%	81.72%	84.75%	65.35%	77.00%	70.28%
As proportion of MMP population with not legal type:							
U.S. migrants	N.A.	16.37%	11.54%	5.19%	21.92%	12.15%	11.33%
Internal migrants	N.A.	6.44%	8.18%	10.67%	16.70%	14.72%	15.91%
Non-movers	N.A.	77.19%	80.27%	84.14%	61.39%	73.14%	72.76%

Table 10: Counterfactual II: No deportation risk (set to 0%)

Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
International migrants	11.63%	14.18%	10.86%	5.04%	20.10%	12.13%	12.01%
Internal migrants	6.15%	7.58%	8.59%	10.73%	17.85%	14.73%	15.52%
Not movers	82.23%	78.24%	80.55%	84.23%	62.04%	73.14%	72.47%
With parents with US experience	14.07%	3.80%	3.49%	2.76%	3.39%	3.41%	4.00%
Educ: 0-6 yrs. of education	40.68%	37.94%	39.85%	87.58%	40.41%	38.92%	39.01%
Educ: 7-9 yrs. of education	42.59%	37.04%	36.47%	7.57%	35.87%	37.05%	36.30%
Educ: >9 yrs. of education	16.73%	25.02%	23.68%	4.85%	23.72%	24.03%	24.69%
Located in enclave	60.08%	58.54%	59.93%	62.18%	57.81%	98.59%	57.35%
Located in California	32.32%	33.78%	34.37%	35.54%	34.73%	56.77%	32.50%
Legal	17.87%	12.13%	18.04%	17.35%	11.09%	4.55%	8.65%
HHI of locations	0.1858	0.1696	0.1739	0.1846	0.1726	0.3572	0.1637
% Legal migrants in enclave	70.21%	72.07%	69.57%	71.71%	69.33%	70.73%	67.18%
% Undocumented migrants in enclave	57.87%	56.68%	57.82%	60.18%	56.38%	99.93%	56.42%
Mean length - international trip	2.44	2.37	2.37	2.38	2.31	2.34	2.36
Mean length - internal trip	0.48	0.77	0.77	0.77	0.70	0.67	0.78
Correlation mig. rate and budget	-0.59	-0.22	-0.24	-0.38	-0.37	-0.34	-0.33

Implied Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
Prop. legal type in MMP	N.A.	24.23%	24.16%	21.78%	19.90%	10.93%	6.37%
As proportion of MMP population with legal type:							
U.S. migrants	N.A.	7.10%	8.10%	4.01%	11.20%	5.05%	16.32%
Internal migrants	N.A.	11.25%	10.18%	11.24%	23.45%	17.95%	13.41%
Non-movers	N.A.	81.65%	81.72%	84.75%	65.35%	77.00%	70.28%
As proportion of MMP population with not legal type:							
U.S. migrants	N.A.	16.45%	11.73%	5.32%	22.31%	13.00%	11.71%
Internal migrants	N.A.	6.40%	8.09%	10.59%	16.46%	14.33%	15.67%
Non-movers	N.A.	77.15%	80.18%	84.09%	61.22%	72.67%	72.62%

Table 11: Counterfactual III: Deportation risk increases to 15%

Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
International migrants	11.63%	13.87%	10.04%	4.48%	18.28%	8.09%	10.01%
Internal migrants	6.15%	7.72%	9.01%	11.06%	18.93%	16.63%	16.78%
Not movers	82.23%	78.42%	80.94%	84.46%	62.79%	75.28%	73.21%
With parents with US experience	14.07%	3.81%	3.58%	2.80%	3.44%	3.55%	4.15%
Educ: 0-6 yrs. of education	40.68%	37.98%	39.56%	92.17%	40.31%	38.88%	38.86%
Educ: 7-9 yrs. of education	42.59%	37.02%	36.53%	4.76%	35.97%	37.03%	36.15%
Educ: >9 yrs. of education	16.73%	25.00%	23.91%	3.06%	23.72%	24.09%	24.98%
Located in enclave	60.08%	58.89%	61.09%	61.95%	59.37%	97.97%	59.93%
Located in California	32.32%	33.96%	34.97%	35.52%	35.73%	57.16%	33.70%
Legal	17.87%	12.41%	19.49%	19.52%	12.19%	6.83%	10.39%
HHI of locations	0.1858	0.1707	0.1776	0.1855	0.1785	0.3620	0.1709
% Legal migrants in enclave	70.21%	72.07%	69.57%	71.71%	69.33%	70.73%	67.18%
% Undocumented migrants in enclave	57.87%	57.03%	59.05%	59.58%	57.99%	99.99%	59.09%
Mean length - international trip	2.44	2.37	2.37	2.38	2.30	2.32	2.36
Mean length - internal trip	0.48	0.77	0.77	0.77	0.70	0.67	0.78
Correlation mig. rate and budget	-0.59	-0.22	-0.22	-0.38	-0.36	-0.35	-0.31

Implied Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
Prop. legal type in MMP	N.A.	24.23%	24.16%	21.78%	19.90%	10.93%	6.37%
As proportion of MMP population with legal type:							
U.S. migrants	N.A.	7.10%	8.10%	4.01%	11.20%	5.05%	16.32%
Internal migrants	N.A.	11.25%	10.18%	11.24%	23.45%	17.95%	13.41%
Non-movers	N.A.	81.65%	81.72%	84.75%	65.35%	77.00%	70.28%
As proportion of MMP population with not legal type:							
U.S. migrants	N.A.	16.03%	10.66%	4.61%	20.04%	8.46%	9.58%
Internal migrants	N.A.	6.59%	8.64%	11.01%	17.80%	16.47%	17.01%
Non-movers	N.A.	77.38%	80.70%	84.38%	62.16%	75.07%	73.41%

Table 12: Counterfactual IV: U.S. wages increase of 10%

Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
International migrants	11.63%	15.61%	12.15%	5.66%	22.32%	12.31%	13.64%
Internal migrants	6.15%	6.93%	7.93%	10.43%	16.57%	14.64%	14.55%
Not movers	82.23%	77.46%	79.92%	83.92%	61.11%	73.05%	71.81%
As proportion of international migrants:							
With parents with US experience	14.07%	3.81%	3.53%	2.81%	3.44%	3.52%	4.01%
Educ: 0-6 yrs. of education	40.68%	37.88%	39.61%	87.25%	40.17%	38.86%	38.84%
Educ: 7-9 yrs. of education	42.59%	37.06%	36.58%	7.78%	36.02%	37.19%	36.43%
Educ: >9 yrs. of education	16.73%	25.06%	23.81%	4.96%	23.81%	23.96%	24.73%
Located in enclave	64.26%	57.07%	58.07%	60.47%	55.98%	98.21%	55.00%
Located in California	32.32%	32.89%	33.17%	34.21%	33.49%	55.62%	30.99%
Legal	17.87%	12.75%	18.69%	18.08%	11.79%	5.31%	8.79%
HHI of locations	0.1858	0.1648	0.1674	0.1770	0.1659	0.3465	0.1566
% Legal migrants in enclave	70.21%	69.65%	67.12%	69.72%	66.39%	68.08%	64.58%
% Undocumented migrants in enclave	57.87%	55.24%	56.00%	58.44%	54.59%	99.91%	54.08%
Mean length - international trip	2.44	2.37	2.37	2.38	2.31	2.34	2.36
Mean length - internal trip	0.48	0.77	0.77	0.77	0.70	0.67	0.78
Correlation mig. rate and budget	-0.59	-0.26	-0.29	-0.42	-0.43	-0.45	-0.40

Implied Moments	Data	(I)	(II)	(III)	(IV)	(V)	(VI)
Prop. legal type in MMP	N.A.	24.23%	24.16%	21.78%	19.90%	10.93%	4.99%
As proportion of MMP population with legal type:							
U.S. migrants	N.A.	8.21%	9.40%	4.69%	13.23%	5.98%	6.81%
Internal migrants	N.A.	10.61%	9.47%	10.88%	22.14%	17.34%	3.93%
Non-movers	N.A.	81.18%	81.14%	84.43%	64.64%	76.68%	89.25%
As proportion of MMP population with not legal type:							
U.S. migrants	N.A.	17.98%	13.03%	5.93%	24.58%	13.08%	4.21%
Internal migrants	N.A.	5.75%	7.44%	10.30%	15.18%	14.31%	5.01%
Non-movers	N.A.	76.27%	83.77%	83.77%	60.24%	72.60%	90.78%

Appendix I: Assignment of U.S. destinations

I aggregate the 50 U.S. states in 10 different locations. I do this in order to have a relative big number of observations per location that allows me to estimate year-location fixed effects in the CPS sample of Mexican workers. I exclude Alaska and Hawaii from the analysis due to the geographical distance between Mexico and these two states.

In most of the cases I follow the Census divisions. Nonetheless, I did changes to adjust to the fact that immigration court jurisdictions might cover more than two Census divisions. Additionally, I merged the original Division I New England and Division II Middle Atlantic of the census, which form part of the census region of Northeast, due to the small number of Mexican individuals in New England for the period 1998-2013. In total, only 480 individuals were surveyed in New England in the 16 years of sample and my location-year fixed effects were unreliable. Finally, I separated the border states: California, Arizona, and the group of Texas (conformed by Oklahoma, New Mexico, and Texas) due to the fact that these states have had historically large numbers of Mexican-born population.

In Table 13, I present the 10 different locations I constructed. In the third column, I present the immigration court that rules in each state. In the last column, the original Census division is presented for comparison.

Table 13: Assignment of destinations in the U.S.

Assignment	State	Immigration court jurisdiction	Original Census Division
Divisions I & II: Northeast	Connecticut	Connecticut	Division I: New England
	Maine	Massachusetts	Division I: New England
	Massachusetts	Massachusetts	Division I: New England
	New Hampshire	Massachusetts	Division I: New England
	Rhode Island	Massachusetts	Division I: New England
	Vermont	Massachusetts	Division I: New England
	New Jersey	New Jersey	Division II: Middle Atlantic
	New York	New York	Division II: Middle Atlantic
	Pennsylvania	Pennsylvania	Division II: Middle Atlantic
Division III: East North Central	Illinois	Illinois	Division III: East North Central
	Indiana	Illinois	Division III: East North Central
	Wisconsin	Illinois	Division III: East North Central
	Michigan	Michigan	Division III: East North Central
	Ohio	Michigan	Division III: East North Central

Table 13: Assignment of destinations in the U.S. (cont'd)

Assignment	State	Immigration court jurisdiction	Original Census Division
Division IV: West North Central	Minnesota	Minnesota	Division IV: West North Central
	North Dakota	Minnesota	Division IV: West North Central
	South Dakota	Minnesota	Division IV: West North Central
	Kansas	Missouri	Division IV: West North Central
	Missouri	Missouri	Division IV: West North Central
	Iowa	Nebraska	Division IV: West North Central
	Nebraska	Nebraska	Division IV: West North Central
Division V: South Atlantic	Florida	Florida	Division V South Atlantic
	Georgia	Georgia	Division V: South Atlantic
	North Carolina	Georgia	Division V: South Atlantic
	South Carolina	Georgia	Division V: South Atlantic
	Delaware	Maryland	Division V: South Atlantic
	Maryland	Maryland	Division V: South Atlantic
	District of Columbia	Virginia	Division V: South Atlantic
	Virginia	Virginia	Division V: South Atlantic
	West Virginia	Virginia	Division V: South Atlantic
	Alabama	Georgia	Division VI: East South Central
Divisions VI & VII: East and West South Central	Mississippi	Louisiana	Division VI East South Central
	Kentucky	Tennessee	Division VI: East South Central
	Tennessee	Tennessee	Division VI: East South Central
	Louisiana	Louisiana	Division VII: West South Central
	Arkansas	Tennessee	Division VII: West South Central
Division VIII: Mountain	Colorado	Colorado	Division VIII: Mountain
	Utah	Colorado	Division VIII: Mountain
	Wyoming	Colorado	Division VIII: Mountain
	Nevada	Nevada	Division VIII: Mountain
Division IX (mod): Northwest	Idaho	Oregon	Division VIII: Mountain
	Montana	Oregon	Division VIII: Mountain
	Oregon	Oregon	Division IX: Pacific
	Washington	Washington	Division IX: Pacific
Arizona	Arizona	Arizona	Division VIII: Mountain
California	California	California	Division IX: Pacific
Texas	Oklahoma	Texas	Division VII: West South Central
	Texas	Texas	Division VII: West South Central
	New Mexico	Texas	Division VIII: Mountain

Appendix II: Borjas algorithm for imputating most likely type

I use the methodology introduced in Borjas (2017) to impute undocumented status for Mexican-born individuals surveyed in the CPS. The algorithm that Borjas (2017) uses assigns a foreign-born person as a "potentially legal" immigrant if any of these conditions applies:

1. The respondent arrived before 1980.
2. The person reports that he or she is a U.S. citizen.
3. The respondent is a veteran, or is currently in the Armed Forces.
4. The respondent works in the government sector.
5. The occupation of the respondent requires some form of licensing (such as physicians, registered nurses, air traffic controllers, and lawyers).
6. The spouse of the respondent is a legal immigrant or U.S. citizen.
7. The person resides in public housing or receives rental subsidies, or the person is a spouse of someone who resides in public housing or receives rental subsidies.
8. The person reports that he or she receives Social Security benefits, SSI, Medicaid, Medicare, or Military Insurace.

One situation that might bias the computation of the number of undocumented and legal Mexican individuals at the state level is the existence of state policies that affect the accessibility of undocumented immigrants to public services like Medicaid and public housing. For robustness, I additionally compute the number of legal and undocumented immigrants by assigning a "potentially legal" type only to individuals in the CPS that comply with one of the requirements enlisted in points 1 through 6. There is not substantial difference in the estimated number of "potentially undocumented" migrants across locations in the robustness check.

Appendix III: Reduced form regressions for residing in historically most preferred location of source community

As a motivation for the inclusion of a utility term of being in the preferred historical destination of your community, I run the following Linear Probability Model based on the labor history of MMP migrants in the US:

$$Y_{ijkt} = \alpha_i + \beta_1 \text{Legal}_{it} + \beta_2 \text{USExperience}_{it} + \beta_3 \text{EstNoTrips}_{it} + \beta_4 \text{Married}_{it} + \delta_{kt} + \mu_j + \varepsilon_{ijkt}$$

where in the main specification $Y_{ijkt} = 1$ if individual i surveyed in origin community j was located in the historically preferred U.S. division k at time t, and $Y_{ijkt} = 0$ otherwise. I have also included in the regression individual fixed effects captured by α_i, and important individual variables that vary across time like legal status ($\text{Legal}_{it} = 1$ if i has valid documents to be in the U.S.), U.S. cumulative experience in years up to year t (USExperience_{it}), estimated number of U.S. trips done up to time t (EstNoTrips_{it}), and marital status ($\text{Married}_{it} = 1$ if i is married at time t).

Additionally, δ_{kt} are fixed effects by division and year that capture transitory shocks at the different destinations. For example, a relevant change in immigration policy in the state of Texas for a certain period of time would be captured by this fixed effect. Finally, I have included fixed effects at the community level μ_j to incorporate heterogeneity on the migration patterns across communities in Mexico.

The results of the regression are in Table 14. I have included observations of individual i only when he is present in the U.S. From the second column, one can conclude that passing from undocumented to legal status is associated with an increase of 1.93% on the probability of a male individual of residing in the preferred historical U.S. location of his community. For locations defined as divisions (Appendix I), the probability increases by 1.54% but it is not statistically significant at the 5% level. However, the standard errors are conservative and have been clustered at the community level.

Table 14: Reduced form regression for placement in historically preferred destination in the U.S.

	(1)	(2)
Dep. Ver: Y = 1 if located in historically preferred location in the U.S.	Division	State
Married	0.0054	-0.0013
	(0.0080)	(0.0072)
USExperience	8.61e-05*	8.33e-05*
	(5.09e-05)	(4.88e-05)
EstNoTrips	-0.0006	8.32e-05
	(0.0021)	(0.0022)
Legal	0.0154	0.0193**
	(0.0100)	(0.0097)
Individual fixed effects	Yes	Yes
Source community fixed effects	Yes	Yes
Location-time fixed effects	Yes	Yes
Observations	29,316	29,316
Number of different migrants	4,842	4,842

Robust standard errors clustered by source comunity in parentheses

***p< 0.01, **p< 0.05, *p< 0.1