The Effect of Work Visas on Unauthorized Immigration*

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Abstract

We examine how increasing the number of work visas available to potential migrants would affect the flow of unauthorized immigrants to the U.S. In particular, U.S. policy currently bans people who are deported from receiving legal status in the future. This aims to serve as an extra deterrent effect, but may be ineffective given that the probability of being able to move to the U.S. legally is very low for most people in Mexico. To explore this, we develop a dynamic discrete location choice model, which we estimate using data from the Mexican Migration Project. We consider various counterfactual policies that vary the intensity of enforcement and access to work visas. The results highlight an important policy interaction in which increased deportations and increased opportunities for legal migration reinforce one another to lower unauthorized migration rates. These findings have important implications for structuring future immigration reforms.

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1 Introduction

Approximately 8 million unauthorized immigrants have been present in the U.S. workforce in each year since 2005 (Passel and Cohn 2018). U.S. employers demand these workers' services in spite of the significant barriers to employment facing unauthorized workers and potential sanctions facing their employers. Because U.S. immigration policy is quite restrictive, the vast majority of potential immigrants can only reside and work legally in the U.S. if they have a close family member who is a U.S. citizen or permanent resident.[1] In this project, we ask how increasing the number of work visas available to potential immigrants would affect the flow of unauthorized immigrants to the U.S.

U.S. immigration law states that in many cases an immigrant who was formally deported from the U.S. cannot reenter for any reason, including for family reunification or via a work visa.[2] Given this policy environment, immigration enforcement through deportation discourages unauthorized migration to the U.S. through at least two channels. First, a higher probability of deportation directly reduces the expected value of moving to the U.S., since there is an increased probability of being removed to Mexico before the individual would have chosen to return. Second, deportation results in a loss of the option value of migrating legally in the future. As the baseline probability of receiving legal status increases, this second channel becomes more important. Therefore, the policy of banning deportees from returning to the U.S. creates a complementarity between enforcement measures that increase the probability of deportation and immigration policies that expand the available options for legal migration. We quantify this channel using detailed data on potential migrants' location choices and legal status in a dynamic discrete location choice framework.

Specifically, we construct a simplified version of the setup in Lessem (2018).[3] Potential Mexican migrants are forward looking, and in each period choose whether to live in Mexico or the U.S. in order to maximize the expected discounted value of their lifetime utility. They take into account the utility of living in each location given their education and legal status, the cost of moving, the probabilities of deportation and legalization, and their idiosyncratic payoff to living in each location. We estimate the model using data from the Mexican Migration Project (MMP), which provides unparalleled detail regarding the migration histories of migrants between Mexico and the U.S. Importantly, the MMP data include information on the timing of migration events and changes in legal status, showing that many migrants move temporarily, making the dynamic nature of the model essential to accurately understanding the implications of migration policy for migration decisions.

After estimating the model using maximum likelihood, we consider various counterfactual poli-

[1] In 2016, 68 percent of those obtaining legal permanent residence in the U.S. did so through family-based preferences, while only 12 percent did so under employment-based preferences (DHS 2017).

[2] See footnote 13 for specifics of the entry ban policy for those formally removed from the U.S.

[3] In Lessem (2018), individuals choose from a set of locations in the US and Mexico, building off of Kennan and Walker (2011), who developed and estimated a dynamic discrete choice model of internal migration in the US.

cies that alter deportation rates and the probability that a potential migrant receives legal status in the U.S. The results are consistent with complementarity between deportation rates and increased probability of legal status when deportees are banned from reentering the U.S. As expected, increasing the deportation rate reduces the rates of unauthorized migration to the U.S. and the cumulative number of years a potential migrant spends living in the U.S. as an unauthorized immigrant. However, these effects are larger when the probability of gaining legal status is higher, confirming the importance of losing the opportunity to legally move to the U.S. and highlighting the interactions between enforcement and visa policies.

In spite of broad agreement in the policy community that expanded labor market access would reduce unauthorized immigration, we are aware of no systematic evidence regarding the likely magnitude of the effect of expanding legal work opportunities.[4] Instead, prior work has focused on how unauthorized immigration responds to changes in enforcement, including border enforcement personnel, border barriers, interior deportation policies, and state-level immigration policies.[5] In contrast, we examine the interactions between enforcement and visa policies, comparing a variety of alternative policy options in the context of counterfactual simulations.

Our findings are important for contemporary immigration policy debates. Specifically, the complementarity between enforcement and legal immigration policy informs the choice of whether to enact different types of immigration policies simultaneously or sequentially. Many of the comprehensive immigration reforms that have been proposed in the past 25 years include increases in enforcement and expanded guest worker programs that would begin simultaneously.[6] Our results suggest that these policies would reinforce one another in reducing unauthorized immigration to the U.S. However, an alternative approach requires reductions in unauthorized migration prior to increasing the options for legal migration. This sequential approach is implemented in practice either through the use of "trigger" clauses within a single piece of legislation or by proposing legislation focused exclusively on enforcement prior to separate legislation expanding the options for legal immigration.[7] While there may be other justifications for the sequential approach, our

[4] Massey, Durand, and Malone (2002) speculate that the Bracero guest worker program, in place during 1942-1964, may have caused the observed decline in border apprehensions during that time period.

[5] For example, among many others, Hanson and Spilimbergo (1999), Bohn and Pugatch (2015) and Lessem (2018) study changes in Border Patrol resources, Bohn, Lofstrom, and Raphael (2014) and Caballero, Cadena, and Kovak (2018) study an Arizona law reducing employment opportunities for unauthorized immigrants, Feigenberg (2017) and Allen, Dobbin, and Morten (2018) study border barriers between Mexico and the U.S., and East et al. (2018) and East and Velasquez (2019) study the effects of deportations under the Secure Communities program.

[6] For example, see the W-Visa low-skilled guest worker program proposed in the "Border Security, Economic Opportunity, and Immigration Modernization Act," Senate Bill S.744, in July 2013.

[7] There are many examples of "triggers" in recent comprehensive reform proposals. In the "Secure Borders, Economic Opportunity, and Immigration Reform Act" of 2007 (S.1639), unauthorized immigrants would only have received access to an expanded guest worker program 18 months after the appropriation of funds for an employment verification system. In the "Border Security, Economic Opportunity, and Immigration Modernization Act" of 2013 (S.744), formerly unauthorized immigrants could seek legal permanent residence only following deployment of additional Border Patrol agents, construction of additional border fencing, and other enforcement investments, with the objective of a 90% apprehension rate for attempted border crossings. An example of the border-security-first

findings suggest that achieving a target reduction in unauthorized migration will be more costly in the absence of increased legal access to the U.S. than when implementing both sets of policies simultaneously. More broadly, if increasing legal access to the U.S. labor market substantially reduces unauthorized immigration, then it may help reduce other enforcement costs, and the reduced numbers of immigrants crossing the border illegally to work in the U.S. would also make it easier to identify those involved in drug or weapons smuggling.

Our paper proceeds as follows. Section 2 summarizes the relevant aspects of U.S. immigration policy, highlighting aspects that drove important decisions in constructing and estimating our model. Section 3 describes the Mexican Migration Project data and provides summary statistics. Sections 4 and 5 describe the model and estimation. Section 6 presents the results, including measures of model fit and the results of counterfactual simulations, and Section 7 concludes.

2 Policy background

Since 1965, U.S. immigration policy has largely been based upon a categorical preference system focused on admitting close relatives of U.S. citizens and prior immigrants and those with skills deemed valuable to the U.S. labor market.[8] Individuals may be admitted to the U.S. as lawful permanent residents or as temporary residents or visitors. About two-thirds of those gaining permanent residence fall under family-based categories of admission, either immediate relatives of U.S. citizens (spouses, parents, and unmarried children), or under family-sponsored preferences covering adult children and siblings of U.S. citizens or immediate relatives of lawful permanent residents (CBO 2010). Other paths to permanent residence include employment-based preferences covering highly skilled workers, those with advanced degrees or extraordinary abilities, and investors; humanitarian admissions covering refugees, asylum seekers, and those covered by source-country-specific humanitarian programs; and the diversity lottery program providing permanent residence to individuals from countries with historically low rates of U.S. immigration.

There are many categories of temporary visas, covering tourists, temporary workers, students, and many others. Of particular relevance to our study are the temporary worker programs, which cover highly skilled workers (H-1) or other workers in agriculture (H-2A) and services (H-2B). The latter programs for less-skilled temporary workers are quite small, accounting for only 537,150 admissions in fiscal year 2017 (DHS 2017). The small scale of these programs implies that potential immigrants without advanced degrees and without close relatives in the U.S. have very few opportunities to pursue lawful residence and employment in the U.S.

Partly due to the limited options available to less-educated Mexican migrants seeking to work in the U.S., since the 1970s a significant number of Mexican-born individuals have moved to the U.S.

approach is the "Border Security and Immigration Reform Act" of 2018 (H.R.6136), which would have increased border security funding significantly without expanding legal immigration channels.

[8]See CBO (2006) for an accessible review of current and past U.S. immigration policy.

as unauthorized immigrants. Unauthorized immigrants may enter the U.S. by crossing the border between ports of entry, by being smuggled through a port of entry, or by entering legally on a temporary visa and staying in the U.S. after the visa's expiration. Estimating the number of unauthorized immigrants is difficult due to the lack of administrative records for unauthorized migrants, but a standard approach is to use household survey data to estimate the total number of foreign-born individuals residing in the U.S. and then subtract the number of authorized immigrants based on administrative data. Figure 1 shows two such measures of the unauthorized immigrant population, one constructed by the Pew Research Center and another showing official estimates produced by the Immigration and Naturalization Service and the Department of Homeland Security.[9] In spite of slight differences in the samples and other choices, the two data sources provide remarkably similar estimates for the unauthorized population in each year. The unauthorized population fell between 1986 and 1989 before increasing steadily until the onset of the Great Recession in 2007, after which the unauthorized population has been relative stable around 11 million.

The significant growth in the unauthorized immigrant population prompted a number of attempts to address the issue. Most prominent among these is the Immigration Reform and Control Act of 1986 (IRCA), which provided legal permanent residence and the possibility of citizenship for more than 3 million previously unauthorized immigrants, more than 2 million of whom were from Mexico (Massey, Durand, and Malone 2002). IRCA provided two paths to legal status, one requiring applicants to show continuous residence in the U.S. since January 1, 1982, and a Special Agricultural Worker program for those who worked for at least 90 days on certain specified crops during the 1985-86 season. It also strengthened enforcement measures, with a 50 percent increase in the enforcement budget of the Immigration and Naturalization Service and, for the first time, imposing sanctions on employers knowingly hiring unauthorized workers (Massey, Durand, and Malone 2002). The law's passage was generally viewed as a surprise, following a decade of failed attempts at reform, so it is unlikely that migrants or other agents anticipated its arrival (Cascio and Lewis 2019). The effect of IRCA in legalizing a significant share of the previously resident unauthorized immigrant population is visible in Figure 1 between 1986 and 1990, but the subsequent years make clear that the policy did not have the intended effect of reducing unauthorized immigration in the long run.

The ensuing decades saw various attempts at reducing unauthorized immigration to the U.S., generally through increasing border enforcement, including personnel, physical barriers, and technology to detect illegal crossing, and additional resources for interior enforcement such as workplace raids. Figure 2 shows border enforcement budgets and the number of Border Patrol staff assigned to the "Southwest Sectors" along the U.S.-Mexico border.[10] Both series exhibit very large increases

[9]See Appendix B.2 for details on these data. Note that the official government estimates were produced by the Immigration and Naturalization Service prior to 2003 and by the Department of Homeland Security (DHS) Office of Immigration Statistics thereafter, following the creation of DHS in 2003.

[10]Figure 2 shows the budget for the Immigration and Naturalization Service (INS) and the combined budgets of

in enforcement resources starting in the mid 1990s and continuing through the late 2000s. Of particular interest for this study is the Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA) of 1996.[11] As with other policies enacted during the 1990s, IIRIRA increased border enforcement and limited immigrants' access to public programs and services. However, it also broadened the options available for law enforcement seeking to deport unauthorized immigrants, and strengthened reentry bans for those violating immigration law under various circumstances.

IIRIRA expanded the ability of enforcement officers to directly remove unauthorized immigrants, without a hearing before an immigration judge, and limited immigrants' ability to request waivers or to appeal decisions.[12] These non-judicial removal processes made it much easier for enforcement agencies to formally remove unauthorized immigrants who previously might have been allowed to return informally, through a "voluntary departure" or "withdrawal of application for admission." This distinction is particularly important; after a formal removal the individual is not allowed to reenter the U.S. for any reason for a specified period of time, i.e. they lose access to the possibility of legal immigration.[13] Those departing informally do not face these reentry bans. Figure 3 shows the numbers of formal removals (which result in reentry bans) and informal returns (which do not) on the left axis, along with removals' share of the total on the right axis. Formal removals became much more prevalent starting in 1997, and constituted more than 70 percent of the total in recent years, meaning that the vast majority of removals were subject to entry bans.

The combination of increased reliance on formal removals and entry bans for formally deported individuals leads to the primary mechanism we examine in this paper. When those apprehended migrating illegally are banned from migrating legally in the future, the deterrent effect of immigration enforcement will depend upon the baseline probability that one can obtain legal status. The lost option value of legal immigration will be larger when obtaining legal status is more likely, increasing the deterrent effect of enforcement. In Sections 4 – 6 we estimate a model and generate counterfactuals allowing us to investigate these interactions between immigration enforcement and legal immigration policies.

Customs and Border Protection (CBP) and Immigration and Customs Enforcement (ICE), which took over INS enforcement functions following the creation of the Department of Homeland Security in 2003. Both series are presented in year-2015 dollars.

[11]See Rosenblum et al. (2014) for a thorough summary of IIRIRA, upon which this discussion of IIRIRA is based.

[12]Such procedures include "expedited removal" for those arriving in the U.S. without valid entry documents, "reinstatement of removal" for those who illegally reenter after a previous removal, and "administrative removal" for those without lawful permanent residence who commit aggravated felonies.

[13]Those deported through expedited removal are ineligible for a visa for 5 years, those removed through standard procedures are ineligible for 10 years, those removed a second time after apprehension at arrival are ineligible for 20 years, and those removed a second time after re-entering the U.S. are permanently barred. Moreover, those apprehended after re-entering the U.S. after a removal order may be subject to criminal charges, rather than civil charges as in most cases involving violations of immigration law. See Rosenblum et al. (2014) for additional detail.

3 Data

We use data from the Mexican Migration Project (MMP), a joint project of Princeton University and the University of Guadalajara.[14] The MMP is a repeated cross-sectional dataset that was first collected in 1982 and is still ongoing. In each year, a few target communities in Mexico are selected, and a random sample of households is surveyed in an effort to understand the circumstances, decisions, and outcomes related to international migration for Mexican individuals. To our knowledge, this is the most detailed source of information available on migration decisions between the U.S. and Mexico. Although the survey is cross-sectional, it asks respondents about their entire migration history, recording detailed information on when each individual lived in Mexico or the U.S. and whether and when they had legal authorization to reside in the U.S. We are aware of no other large scale data source that provides this level of detail on migration and legal status, both of which are essential to our analysis.

Although the MMP sample is representative of the communities surveyed in a given year, the dataset is not representative of Mexico as a whole, since the survey has oversampled communities with historically high rates of migration to the U.S. For example, the early years of the survey oversampled relatively rural communities in Western-Central Mexico with high historical migration rates.[15] Over time, however, the MMP sampling frame has shifted to other areas in Mexico, including those with lower migration rates. Since the MMP collects retrospective data on migration and legal status, we can still observe migration behavior in early years for individuals in the communities that were surveyed more recently, mitigating representativeness concerns somewhat. Another restriction of the MMP data is that the sample largely only captures a relatively small number of permanent migrants to the U.S. Although the MMP does survey some individuals who have moved to the U.S., this represents a small share of the survey sample.

We utilize MMP data collected in 1997 and later because earlier waves of the survey omitted information on migrants' legal status in the U.S. We also consider retrospective migration and legalization information from 1980 onward in order to avoid earlier years in which migration patterns may have been quite different from those in more recent years. We focus on individuals born in Mexico and restrict the sample to household heads in order to take advantage of the extensive migration and legalization histories the MMP reports for them. In doing so, we abstract from joint household migration decisions.[16] We focus on migration decisions for individuals age 18 to 65 and omit those already in the U.S. by age 18 in order to avoid migration decisions that may be heavily influenced by family members. Finally, we omit a small number of observations exhibiting inconsistencies or missing key information, such as location, education, and legal status.

[14] The data are publicly available at `mmp.opr.princeton.edu`

[15] Appendix Figure B1 shows a map with the current coverage of the survey.

[16] See Gemici (2011) and Lessem (2018) for papers with dynamic models of migration decisions in which an individual's migration decision is influenced by those of family members.

We present summary statistics for our sample in Table 1. Panel (a) shows the characteristics of the household heads in our sample, as observed in the year of the survey (i.e. with one observation for each individual). We observe 14,676 individuals across all years of the survey from 1997 to 2018. 87 percent of the sample is male, and the majority of individuals is between age 30 and 59 in the survey year. We split the sample by years of education, grouping people as low education (0-2 years), middle education (3-11 years), or high education (over 12 years). Reflecting the educational distribution of the broader Mexican population, 67 percent of the sample has 3 to 11 years of education. The vast majority of the sample is surveyed in Mexico, but 5.2 percent is surveyed in the U.S., while 2.8 percent of the sample has legal authorization to reside in the U.S. in the survey year.

Panel (b) uses the retrospective panel dimension of the survey to measure migration patterns. We observe 4,694 Mexico to U.S. migration events between 1980 and 2018. The vast majority (81 percent) never migrated to the U.S. prior to being surveyed by the MMP, 12.7 percent of individuals migrated north once, and the remaining 6.3 percent migrated 2 or more times. Most observed spells of time living in the U.S. were relatively short, with 48 percent of spells lasting only one year. However, there is a long tail, with 20.7 percent of spells lasting 5 or more years, 10.4 percent lasting 10 or more years, and 2.9 percent lasting 20 or more years. This pattern reflects the diversity of migration experiences for Mexican migrants to the U.S., with many individuals migrating for a short time, often visiting repeatedly for seasonal work, and more recent migrants who tend to stay in the U.S. for a longer period of time, particularly as border enforcement has increased.

We now describe yearly migration rates in more detail. Figure 4 examines Mexico to U.S. migration separately for those with or without legal authorization to reside in the U.S. Panel (a) shows the share of those in Mexico and *without* U.S. legal status in year $t-1$ who migrated to the U.S. in year t. Panel (b) shows the same northward migration rate for those *with* U.S. legal status in year $t-1$. A few patterns are apparent. First, people with the ability to move legally migrate to the U.S. at much higher rates. We also see fluctuations over time, most notably high migration rates in both directions in the 1990's and early 2000s and lower migration rates in 2010 and later, following the U.S. Great Recession.[17] Figure 5 performs a similar exercise, measuring the share of those in the U.S. in year $t-1$ who return to Mexico in year t separately by legal status in period $t-1$. The results largely mirror those for northward migration, with authorized immigrants less likely to return to Mexico. Together, the results in Figures 4 and 5 demonstrate the importance of accounting for cyclical factors that may influence the incentive to move between the U.S. and Mexico during different portions of the sample period.

The retrospective panel nature of the MMP also allows us to observe when Mexican individuals

[17] Due to the MMP's retrospective panel structure, the sample sizes are largest in the middle of the sample period. In early years fewer migrants who were surveyed in later years had already reached age 18, while few surveys are able to observe migration events later in the sample.

obtain legal status in the U.S. Figure 6 plots the probability of receiving legal status in each year. To be precise, it shows the share of those without legal status in year $t-1$ who get legal status in year t. It is clear that legalization rates are generally quite low, with the exception of the years immediately following the passage of IRCA in 1986. The dashed black line shows legalization probabilities omitting those reporting receiving legal status under IRCA, and shows that in the absence of this policy, legalization rates were quite consistent over time, averaging around 0.05 percent per year. However, the overall legalization rate was an order of magnitude larger during the IRCA implementation period of 1987-1991. Therefore, when parameterizing the model in Section 5, we allow the legalization rate during 1987-1991 to differ from the rate in other years, and the estimates confirm the much higher legalization rate during these years.

As a final piece of descriptive evidence influencing the modeling choices in the following section, we consider the choice to apply for legal status in the U.S. Starting in the 1997 survey, the MMP records when an individual applied for legal status along with the date, if any, when legal status was granted. When analyzing this information, it became clear that there was little distinction between applying for legal status and obtaining it. 85 percent of those ever applying for legal status received it by the survey year, and more than 90 percent of individuals who eventually received legal status did so within 3 years of applying. It appears that potential migrants in the MMP sample only apply for legal status when they know they are very likely to be approved and when that approval is likely to come quickly, so the application information available in the MMP data provided little information beyond what is already present in the information on realized legal status.

4 Model

Our model is based on a simplified version of the setup in Lessem (2018), in which there are only two locations: the U.S. and Mexico. A person starts each period knowing their legal status and their prior period location. They then receive a set of payoff shocks to living in each location and decide whether to live in the U.S. or Mexico, considering the utility of living in a location, the cost of moving, the payoff shocks to each location, and the expected continuation value of living in that location. If they currently lack legal status in the U.S., they may be granted legal status in the future with some probability, which we will estimate. Consistent with the MMP data, we assume that legal status is an absorbing state, so once a person is granted legal status they do not lose it. In addition, unauthorized immigrants may be deported, in which case they are forced to return to Mexico.

The timing of the model is as follows. People start the period knowing their prior location and legal status for this period. They learn their payoff shocks and decide where to live. If they choose to live in the U.S., they are deported with some probability, which forces them to return to Mexico. At the end of the period, if they previously did not have the ability to move to the U.S. legally, with some probability they get a visa that enables them to move to the U.S. legally should they choose to do so a subsequent period.

The state space includes a person's prior location $j_{t-1} \in \{\text{M}, \text{US}\}$, their legal status at the start of the period ls_t ($= 1$ if legal and 0 otherwise), their fixed characteristics X, their age a_t, and their set of preference shocks η_t. The value function is written as follows:

$$V_t\left(j_{t-1}, ls_t, X, a_t, \eta_t\right) = \max_{k \in \{\text{M}, \text{US}\}} v_t\left(k, j_{t-1}, ls_t, X, a_t\right) + \eta_{kt} \ , \tag{1}$$

A person chooses the location k with the highest valuation each period, where the valuation has a deterministic component, which we denote as $v_t(\cdot)$, and a random component, which we denote as η_t. We assume that the random shocks follow the type I extreme value distribution.

The following expressions show the the deterministic component of choosing location k. First, consider an individual who already has legal status, $ls_t = 1$.

$$\begin{aligned} v_t\left(k, j_{t-1}, ls_t = 1, X, a_t\right) &= u_t\left(k, ls_t, X\right) - MC_t\left(k, j_{t-1}, ls_t, X\right) \\ &+ \beta E_t V_{t+1}\left(k, ls_{t+1} = 1, X, a_{t+1}, \eta_{t+1}\right) \ . \end{aligned} \tag{2}$$

The first component on the right side of equation (2) is the utility of living in a location, which we assume depends on legal status and characteristics. We will explain the parameterization of the utility function in the estimation section, but for now it is useful to think about utility differences across locations arising from two sources: wage differentials between the two countries and preference to live in one's home country, likely due to the presence of one's family, familiarity with the culture, etc. The second component of equation (2) is the cost of moving between locations. This is normalized to equal 0 if a person does not change locations. We allow the cost of moving to vary with legal status, given that it is more costly for unauthorized immigrants to cross the border, since they will have to evade detection. Note that both the utility function and moving cost function have t subscripts, meaning that we will allow them to vary over time. This could reflect changes in the relative wage distribution between the two countries, aggregate business cycle fluctuations, or changes in U.S. policy, including enforcement. The last component of equation (2) is the expected continuation value, maintaining legal status since it is an absorbing state.

Those without legal status ($ls_t = 0$), additionally consider the possibility that they may receive legal status in the next period, with probability $p^l_{t+1}(X)$. This legal status transition may occur whether the individual chooses to live in Mexico or the U.S., and only depends on year and characteristics. However, if an individual without legal status chooses to live in the U.S., they face the additional possibility of deportation, with probability p^d_t.[18] Therefore, the deterministic component

[18]We assume this probability is constant across demographic groups and only varies over time.

of choosing to live in Mexico for those without U.S. legal status is

$$\begin{aligned} v_t\left(k=\text{M}, j_{t-1}, ls_t=0, X, a_t\right) &= u_t\left(k, ls_t, X\right) - MC_t\left(k, j_{t-1}, ls_t, X\right) \\ &+ \beta\, p^l_{t+1}\left(X\right) E_t V_{t+1}\left(k, ls_{t+1}=1, X, a_{t+1}, \eta_{t+1}\right) \\ &+ \beta\left(1-p^l_{t+1}\left(X\right)\right) E_t V_{t+1}\left(k, ls_{t+1}=0, X, a_{t+1}, \eta_{t+1}\right)\ . \end{aligned} \tag{3}$$

The same expression for choosing the U.S. without legal status is

$$\begin{aligned} v_t\left(k=\text{US}, j_{t-1}, ls_t=0, X, a_t\right) &= u_t\left(k, ls_t, X\right) - MC_t\left(k, j_{t-1}, ls_t, X\right) \\ &+ \beta\, p^l_{t+1}\left(X\right)\left(1-p^d_t\right) E_t V_{t+1}\left(k=\text{US}, ls_{t+1}=1, X, a_{t+1}, \eta_{t+1}\right) \\ &+ \beta\, p^l_{t+1}\left(X\right) p^d_t E_t V_{t+1}\left(k=\text{M}, ls_{t+1}=1, X, a_{t+1}, \eta_{t+1}\right) \\ &+ \beta\left(1-p^l_{t+1}\left(X\right)\right)\left(1-p^d_t\right) E_t V_{t+1}\left(k=\text{US}, ls_{t+1}=0, X, a_{t+1}, \eta_{t+1}\right) \\ &+ \beta\left(1-p^l_{t+1}\left(X\right)\right) p^d_t E_t V_{t+1}\left(k=\text{M}, ls_{t+1}=0, X, a_{t+1}, \eta_{t+1}\right)\ . \end{aligned} \tag{4}$$

Note that those who are deported start the subsequent period in Mexico.

To compute the expected continuation values in equations (2) - (4), we need to integrate out future payoff shocks, η_{t+1}. Because we assumed the shocks follow the extreme value distribution, we can solve for a closed form expression for the continuation values. This leads to choice probabilities with the standard logit form:

$$P_t\left(j_t | j_{t-1}, ls_t, X, a_t\right) = \frac{\exp\left(v_t\left(j_t, j_{t-1}, ls_t, X, a_t\right)\right)}{\sum_k \exp\left(v_t\left(k, j_{t-1}, ls_t, X, a_t\right)\right)} \tag{5}$$

Finally, we assume a terminal period $T = 65$, such that $V_{T+1} = 0$ and then solve the model using backward induction.

5 Estimation

5.1 Parameterization

In this section, we parameterize the utility function, moving cost function, and legal status transition function. We write the utility function as follows:

$$u_t\left(j, ls, X\right) = \begin{cases} u^{\text{M}}_{t,X,ls} & \text{if } j = \text{M} \\ u^{\text{US}}_{t,X,ls} & \text{if } j = \text{US} \end{cases} \tag{6}$$

The utility from living in a location $j \in \{\text{M}, \text{US}\}$ may vary arbitrarily by year, individual characteristics X, and legal status. These utilities capture both the intrinsic value of living in a location and the wage one could earn there in a given year.[19] Characteristics X captures individuals' education levels, taking on three possible values reflecting low (0-2 years), medium (3-11 years), and high (12+ years) educational attainment.[20] This allows allow the locations' utility levels to vary by education level, reflecting the possibility that earnings differences across countries likely vary by education level. We condition on legal status, given that the wages for authorized immigrants are likely higher which would give higher utility levels. Conditional on time t, this setup means that we estimate 6 utility parameters for living in each location, given the three different education groups and two possible legal statuses. Each parameter would give the utility from living in a given location with one's current legal status.

We assume that the cost of moving is constant over time,[21] and write the cost of moving from j to k as follows:

$$MC\left(k,j,ls,X\right)=\begin{cases} c_{X,ls}^{\text{M}-\text{US}} & \text{if } j=\text{M} \text{ and } k=\text{US} \\ c_{X,ls}^{\text{US}-\text{M}} & \text{if } j=\text{US} \text{ and } k=\text{M} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

The moving cost when not changing locations is normalized to zero. Moving costs critically depend on legal status, given that it is much easier for authorized immigrants to move to the U.S. We also allow the moving costs to vary with education level, which may affect a person's access to the resources necessary to move between countries.

Next, consider the net utility, defined as the utility minus moving cost, for each potential source-destination pair.

$$\begin{aligned} \tilde{u}_{t,ls,X}^{\text{M}-\text{M}} &\equiv u_t(\text{M},ls,X)-MC(\text{M},\text{M},ls,X)=u_{t,X,ls}^{\text{M}} \\ \tilde{u}_{t,ls,X}^{\text{M}-\text{US}} &\equiv u_t(\text{US},ls,t)-MC(\text{M},\text{US},ls,X)=u_{t,X,ls}^{\text{US}}-c_{t,ls,X}^{\text{M}-\text{US}} \\ \tilde{u}_{t,ls,X}^{\text{US}-\text{M}} &\equiv u_t(\text{M},ls,X)-MC(\text{US},\text{M},ls,X)=u_{t,ls,X}^{\text{M}}-c_{t,ls,X}^{\text{US}-\text{M}} \\ \tilde{u}_{t,ls,X}^{\text{US}-\text{US}} &\equiv u_t(\text{US},ls,X)-MC(\text{US},\text{US},ls,X)=u_{t,X,ls}^{\text{US}} \end{aligned} \tag{8}$$

Instead of estimating the utility and cost parameters separately, we can estimate the net utility parameters $\tilde{u}$, and equation (8) shows how one can then back out the utility and cost parameters.

[19](Lessem 2018) estimates the utility as a function of wages in each location. In that case, the effect of wages on utility was identified by looking at where people move as a function of wages. In the 2 location case, however, if the wage differential is the same for everyone, it is difficult to identify the effect of wages on utility separately from moving costs. This was not a problem in (Lessem 2018) which considered internal migration, as well as a choice of locations in the U.S. We do have variation in the self-reported wage differential across locations for individuals, but in practice that does a poor job of predicting who chooses to migrate, as the people most likely to move do not report the largest wage differentials.

[20]These categories were chosen to reflect natural breakpoints in the Mexican educational distribution and to separate groups with distinct baseline migration probabilities in the MMP.

[21]In future work, we will modify the parameterization to allow for the cost of moving to the US to vary with border enforcement levels.

We need to make a normalization for identification, so we set $\tilde{u}^{\mathrm{M-M}}_{t,ls,X} = 0$. Appendix A shows how these parameters are identified.

Given this setup, we have 3 parameters for each time period, legal status, and education level: the net utility of moving from Mexico to the US, the net utility of moving from the US to Mexico, and the net utility staying in the US. We make some simplifications to maintain a reasonable number of estimated parameters. As mentioned above, we allow the utility and cost parameters to vary by only one demographic characteristic, education, and split the sample into three education groups. Since we also allow the parameters to vary by legal status we have a total of 18 parameters in a given time period (3 parameters per group, 3 education groups, and 2 legal status groups). Our sample covers 39 years (1980-2018), so allowing these parameters to vary across each year would be very computationally costly and would likely overtax the variation available in our data. Instead, we hold the utility and cost parameters in (6) and (7) fixed over time and allow for an additive fixed effect for the utility of living in the U.S. in each of 5 time periods (1980-1993, 1994-2000, 2001-2005, 2006-2009, and 2010-2018). This approach avoids drastically increasing the number of parameters while still allowing the utility values to vary with time, capturing differential business cycles, changes in immigration policy, and other time variation affecting the U.S. and Mexican labor markets differently.

We also parameterize the function characterizing the probability of transitioning to legal status. As stated in the model, we assume that U.S. legal status is an absorbing state, so we only need to consider the probability that a person who previously did not have the ability to move legally is granted a visa in a given period. We write this as

$$p^l_t(X) = p_X + \delta \mathbf{1}(IRCA_t) \tag{9}$$

We estimate a separate legal status transition probability p_X for each of the 3 education groups. Furthermore, we assume that the probability of being granted legal status increases by δ in the IRCA years of 1987-1991. Since this policy was unanticipated, when computing value functions, we assume that $\delta = 0$. However, in the likelihood function, where we consider transitions over legal status, we allow for $\delta \neq 0$, potentially increasing the probability of being granted legal status during the IRCA years, to match the observed rates in the data.

Finally, in equation (4) there is a probability p^d_t of being deported each period. We calculate these deportation rates using data on interior apprehensions of unauthorized immigrants and estimates of the unauthorized population in each year, as described in Appendix B.2. We assume perfect foresight over all changes in deportation rates.

5.2 Likelihood function

Recall that, given the type-I extreme value preference shocks, the probability of choosing a location is given by equation (5). In addition, we estimate the legal transition probabilities, given by equation (9). Denote the function $\tilde{p}_t^l(ls_{t-1}, X)$ as follows:

$$\tilde{p}_t^l(ls_{t-1}, X) = \begin{cases} p_t^l(X) & \text{if } ls_{t-1} = 0 \\ 1 & \text{if } ls_{t-1} = 1 \end{cases} \tag{10}$$

This just states that the legal transition function is given by equation (9) for those who previously do not have the ability to move legally, and those who have legal status will continue to have it in future periods. We write the likelihood function as follows:

$$L(\theta) = \sum_i \sum_0^{T_i} \log \left(P_t\left(j_{it}|j_{i,t-1}, ls_{it}, X_i, a_{it}\right) \times \tilde{p}_t^l\left(ls_{i,t-1}, X_i\right)^{ls_{it}} \times \left(1 - \tilde{p}_t^l\left(ls_{i,t-1}, X_i\right)\right)^{1-ls_{it}} \right) \tag{11}$$

6 Results

We estimate the model using maximum likelihood with data from the MMP, and the resulting parameter estimates are reported in Tables 2 - 4. Table 2 shows the net utility of each choice, conditional on education and legal status. Recall that the utility of staying in Mexico was normalized to zero for each group. Following equation (8), we can use the parameters to back out the utility from living in each location and the cost of moving between locations. Consider people in the middle education group. Since the net utility of staying in Mexico was normalized to zero, and the moving cost is zero when not moving, the utility of living in Mexico is also normalized to zero. The net utility of staying in the U.S. was estimated to be -0.25 for this group, which means that the utility of living in the U.S. is -0.25, since the moving cost in this case is zero. Comparing these estimates, this means that the utility of living in Mexico is higher than the utility of living in the U.S. This is not a surprising result, given that overall migration rates for undocumented immigrants are relatively low (Figure 4 panel (a)). In Lessem (2018) and Kennan and Walker (2011), the utility of living in a location was determined by wages and one's preference for living in their home location. In this case, it seems that the preference for being in Mexico relative to the U.S. is high.

Using equation (8), we can back out the costs of moving to the U.S. and of returning home to Mexico. We find that the return migration cost is essentially 0, and the cost of moving to the U.S. is approximately 5.08. Comparing to legal immigrants with the same education, we see for this group the utility of living in the U.S. is 0.13, which is consistent with the idea that they earn higher wages than unauthorized immigrants. Authorized immigrants' cost of moving to the U.S. is equal to 2.81, which is much lower than for unauthorized immigrants, as expected. The return migration cost for authorized immigrants is approximately 0.98.

Table 3 shows how the utility of living in the U.S. varies with time. These parameters additively shift the relative utility of living in the U.S. and are constant across education and legal status groups within each time period. These time effects do not vary much across years, with the exception of the 2009-2018 period, which is consistent with the decline in net U.S. migration during this time period (see Figures 4 and 5).[22]

Finally, Table 4 shows the estimated legal status transition rates. As expected, these rates increase with education, as there are fewer options for legal migration available to less educated workers. We also see a very substantial increase in transition rates in the IRCA years, consistent with the spike in the share receiving legal status after 1986 in Figure 6. Recall that we assume individuals did not anticipate the increase in legalization probabilities that came with IRCA, but the inclusion of this IRCA effect is important to match the realized increase in transitions from illegal to legal status in the years immediately after IRCA.

Table 5 shows the model fit, comparing average migration rates in the data (columns (1) and (3)) to migration probabilities predicted by the model (columns (2) and (4)). We show the probability of moving to the U.S. and of return migration from the U.S. to Mexico. We see that the model fits the data very well, with predicted migration rates falling with a few tenths of a percentage point of the observed migration rates in all but one case (high-education authorized migrants moving to the U.S.). This close fit between model and data reinforces the credibility of the counterfactuals we describe now.

6.1 Counterfactuals

We use counterfactuals to show the effects of changing both enforcement policies and opportunities to obtain legal status, highlighting the complementarities between these policies. In the estimated model, people believe they can be deported with some probability, which we measure using outside data, as described in Appendix B.2. Individuals also anticipate that they may be granted legal status in future periods, and we estimate these transition rates in the context of the model described above. As discussed in Section 2, when a person is apprehended in the U.S. illegally and formally deported, they lose the ability to move to the U.S. legally for some period of time. Here, we explore how this type of policy affects migration behavior.

We examine a variety of policy options. First, we consider increases in deportation rates. This has a mechanical effect of lowering unauthorized immigration by forcing people to return to Mexico. However, it also influences potential migrants' decisions on where to live. If a person knows that

[22] While migration rates do vary significantly in other time periods, northward and southward migration tend to move together, so net migration is quite constant, until the 2009-2018 period.

they could be forced to return to Mexico if they move to the U.S. illegally, then this lowers the value of moving to the U.S. and can reduce immigration rates for those without legal status. Next, we consider a policy similar to IIRIRA, where if a person has ever been deported, they no longer have any chance of getting a visa that would enable them to move to the U.S. legally, i.e. their legalization probability goes to zero. In theory, this should further reduce immigration rates for a given deportation probability, because deportation both removes an individual from the U.S. and causes them to lose the option value of returning legally in the future. However, given that the estimated legal transition rates are quite low, we anticipate this channel will drive small changes in migration behavior. We then explore what happens in the same situation if the U.S. were to increase the probability of gaining legal status. This should amplify the deterrent effect of increasing deportation rates, since it increases the probability of getting legal status in the future, increasing the value of maintaining that option.

First, we examine how static migration probabilities change in different policy scenarios. Specifically, we compute the probability of moving to the U.S. for a person without legal status, in the middle education group (3-11 years), and age 33 in 2017. The results appear in Table 6. The first row shows the baseline case. We show migration rates for people who have and have not been deported, which are the same in this case because deportations do not affect legal transition rates. In the second row, we now assume that once a person is deported, they no longer have any chance of being granted a visa in future periods. We now should see a difference in the behavior of people who have and have not been deported. On one hand, those who have not been deported have a higher option value of living in the U.S., since there is a positive probability they will be granted legal status in the future. On the other hand, if you have not been deported, there is an extra risk to moving to the U.S., since one could be deported and lose the ability to move to the U.S.. In this case, these effects are small, so migration rates for those with and without a prior deportation appear identical at 2 decimal places. This similarity is driven by the fact that the estimated probability of gaining legal status, shown in Table 4, is sufficiently small that losing the option of migrating legally to the U.S. does not affect behavior.

In the third row of Table 6, we increase deportation rates to 10% per year (well above the observed rates ranging from 1% to 3%, shown in Appendix B.2), without the entry ban policy for deported individuals. We see a 16% reduction in annual migration rates. It is important to note that this reduction is driven entirely by the way the deportation probability affects incentives to move to the U.S.; given how we calculate migration rates they do not include the mechanical effect of deportations moving people back to Mexico. In the fourth row, we impose high deportation rates and entry bans for deported individuals. The effect is again small, because the entry ban policy has minimal deterrent effect when the probability of obtaining legal status is low (Table 4). In the fifth row, we explore what would happen if legal transition rates rose to 1%. In this case, interesting effects emerge. For people who have never been deported, migration rates fall by 3.33%, showing that the entry ban policy starts to have a meaningful impact on migration rates when the probability of obtaining legal status in the future is nontrivial. As expected, there is no effect on those who were already deported, because they have already lost the option of legally residing in the U.S., so the future legalization rate for those not subject to a ban is irrelevant to them.

The changes in migration rates in Table 6 may appear somewhat modest, but small changes in rates can lead to significant changes in stocks. With that in mind, we examine how the various counterfactual policies affect migration decisions over a potential migrant's lifecycle. For each counterfactual policy we explore, we calculate the share of an individual's life (for the years we observe them in the data between the ages of 18 and 65) spent in the U.S., conditional on their legal status. We would like to understand how policy changes affect the decisions of unauthorized immigrants and therefore want to avoid counting reductions in unauthorized immigration that result mechanically from granting more people legal status. We do so by calculating for each individual the i) number of years spent residing in the U.S. without legal status and ii) the total time without legal status, irrespective of location. We then calculate the ratio of these two, yielding the share of time without legal status that the individual spent living in the U.S. The average number of years observed in the data is 9, so we then multiply this share by 9 to estimate the expected number of years spent living in the U.S. without legal status.[23] Because it is based on the share of time without legal status that an individual spends in the U.S., this measure is unaffected by the mechanical reduction in unauthorized migration that occurs when legalization rates increase.

The results for each of the counterfactuals are shown in Table 7. Note that the number of years an individual immigrant spends unauthorized in the U.S. depends on changes in northward and southward migration rates, and the mechanical decline in the number of unauthorized migrants due to deportations. We can see the substantial impact of these combined channels in comparing rows 2 and 3. Increasing the deportation rate to 10% reduces the time spend unauthorized in the U.S. by 36% (from 0.33 years to 0.21). As before, imposing the entry ban for deported individuals has little additional effect in the absence of a significant probability of gaining legal status, even with a high deportation rate (row 4). Finally, in row 5, we impose high deportation rates and increased probability of obtaining legal status. Increasing the probability of obtaining legal status reduces the years spent unauthorized in the U.S. by 5% compared to row 4. This comparison makes clear the complementarity between enforcement policies (increasing the deportation rate) and policies such as guest-worker programs that increase the opportunities for people to migrate legally to the U.S.

[23] This is assuming that each person is an unauthorized immigrant for each of those 9 years. In this case, we estimate the number of years they would live in the US.

7 Conclusion

This paper examines how increasing the number of work visas available to potential migrants would affect the flow of unauthorized immigrants to the U.S. We develop a dynamic discrete location choice model, which we estimate using data from the Mexican Migration Project, and consider a variety of policy counterfactuals to understand the interactions between i) enforcement policies that change the probability of deportation facing unauthorized immigrants and ii) increased access to work visas that increase the probability that a migrant will obtain legal status in the future. Our results make clear that these two sets of policies reinforce one another to lower unauthorized migration rates. Increased deportation rates directly reduce the value of migrating to the U.S. by making it more likely that unauthorized migrants will be forced to return to Mexico before they would have chosen to do so. In the presence of a nontrivial probability of receiving legal status, the costs of deportation are even larger because deportation also causes migrants to lose access to the possibility of migrating to the U.S. legally in the future. Our findings inform ongoing debates about how to structure immigration reforms designed to address the issue of unauthorized migration. Because enforcement and work visa policies reinforce are complementary, implementing them together will likely have a larger impact on unauthorized immigration than would alternative approaches that seek to achieve enforcement goals prior to expanding the options for legal immigration.

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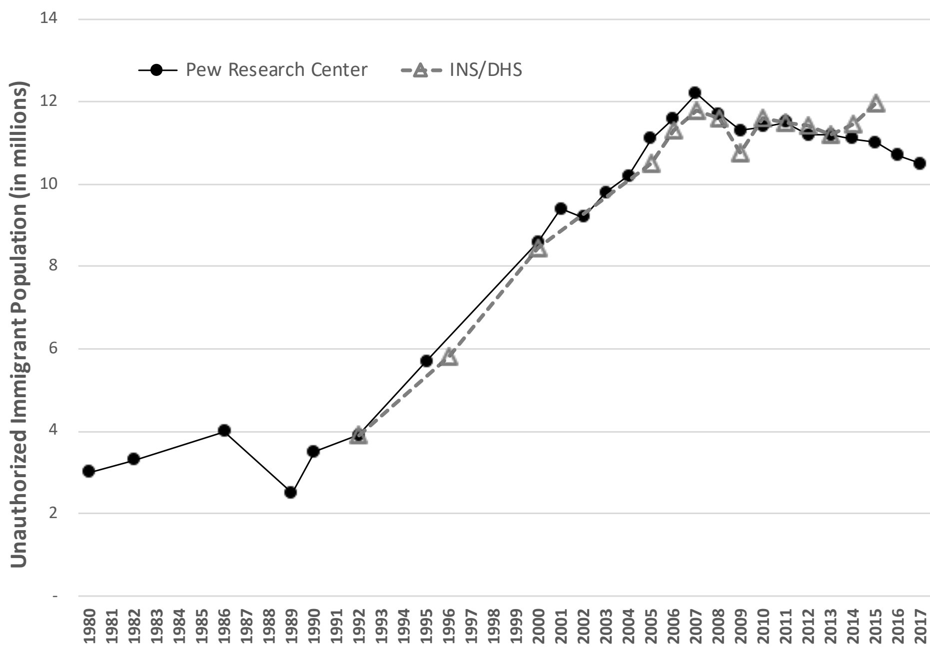
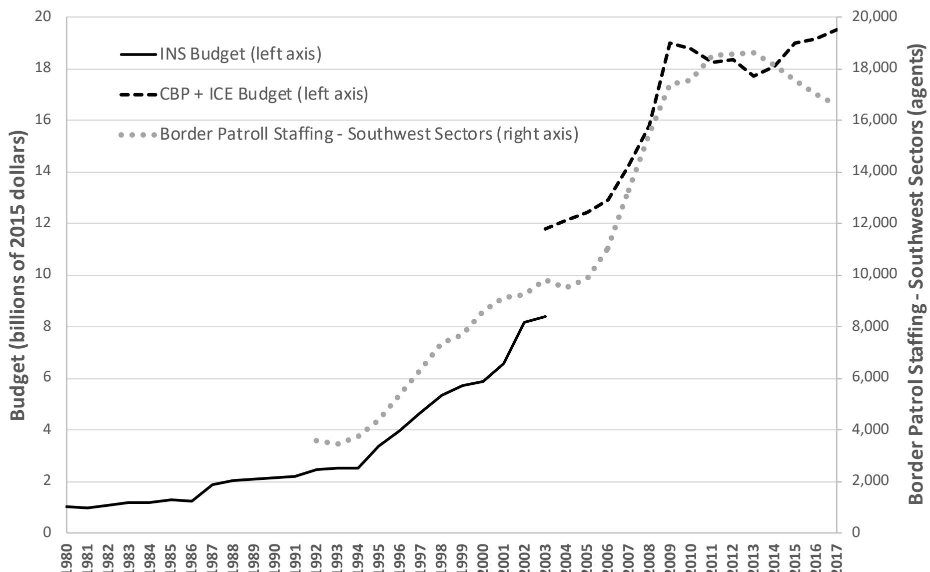
Figures and Tables

Figure 1: Unauthorized Immigrant Population Measures



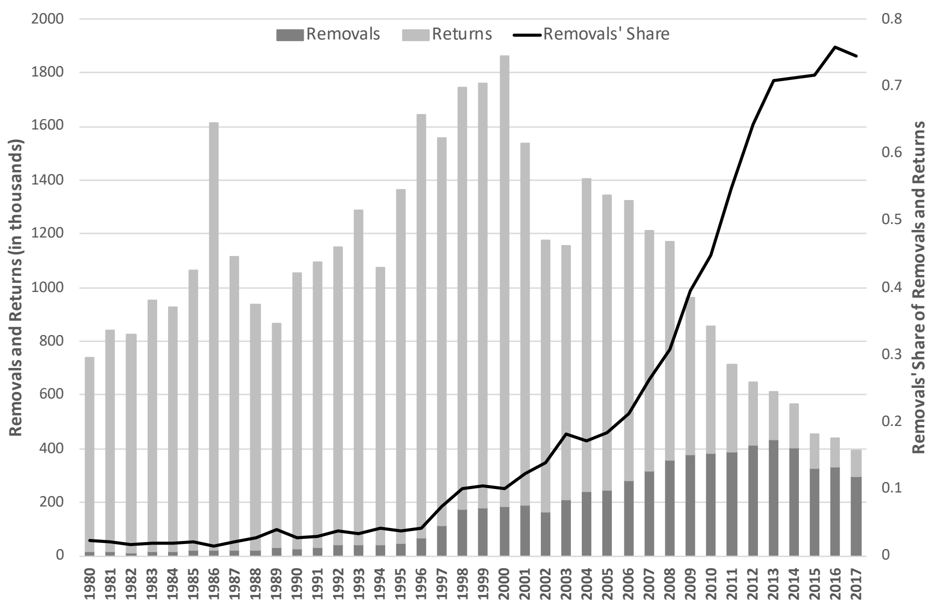
Sources: Both the Pew Research Center and INS/DHS series estimate the unauthorized immigrant population using a residual method, in which administrative measures of the number of authorized immigrants is subtracted from a survey-based estimate of the total foreign-born population. For the Pew Research Center series, estimates for 1990, 1995, 2000, and 2005-2017 are from `https://www.pewresearch.org/hispanic/2019/06/03/facts-on-u-s-immigrants/`; estimates for 1980, 1982, 1986, 1989, and 1992 are from `https://www.pewresearch.org/hispanic/2006/03/07/ii-unauthorized-migrants-the-numbers/`; and estimates for 2001-2004 are from `https://www.pewresearch.org/hispanic/2008/10/02/trends-in-unauthorized-immigration/`. For the INS/DHS series the estimate for 1992 is from `https://www.dhs.gov/sites/default/files/publications/Unauthorized%20Immigrant%20Population%20Estimates%20in%20the%20US%201996.pdf`; the estimate for 1996 is from `https://www.dhs.gov/sites/default/files/publications/Unauthorized%20Immigrant%20Population%20Estimates%20in%20the%20US%201990%20to%202000.pdf`; estimates for 2000 and 2005-2009 are from `https://www.dhs.gov/sites/default/files/publications/18_1214_PLCY_pops-est-report.pdf` using the 2000 Census, while 2010-2015 are from the same source using the 2010 Census.

Figure 2: Border Enforcement Resources



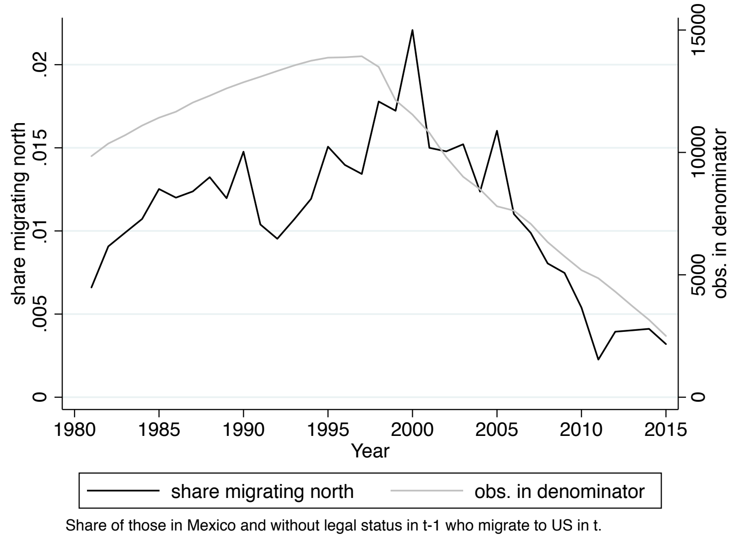
Sources: Immigration and Naturalization Service (INS) Budget for 1980-2003 from `https://www.justice.gov/archive/jmd/1975_2002/2002/html/page104-108.htm`. Customs and Border Protection (CBP) and Immigration and Customs Enforcement (ICE) Budgets for 2003-2017 from yearly Department of Homeland Security Budgets-in-Brief, available at `https://www.dhs.gov/dhs-budget`. Both are reported in billions of year-2015 dollars (left axis) using the CPI-U yearly price deflator. Border Patrol staffing numbers for the Southwest Sectors (right axis) from the U.S. Border Patrol Fiscal Year Staffing Statistics, available at `https://www.cbp.gov/document/stats/us-border-patrol-fiscal-year-staffing-statistics-fy-1992-fy-2018`.

Figure 3: Removals and Returns

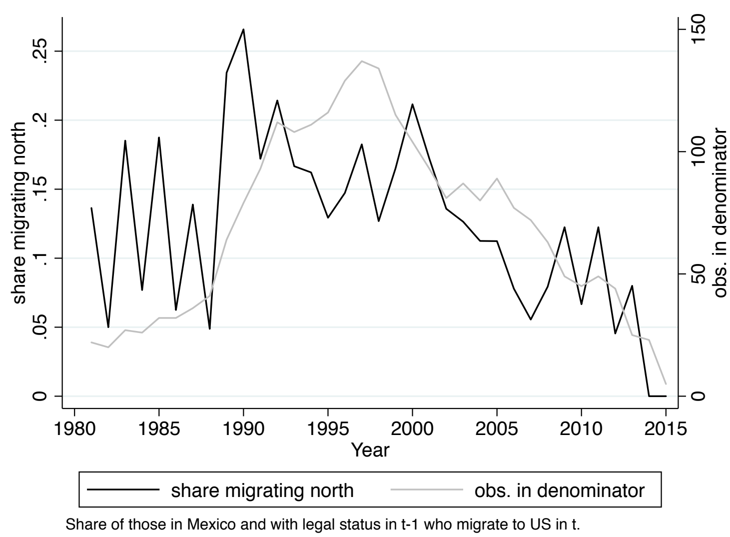


Sources: Table 39 of the 2017 Yearbook of Immigration Statistics, available at `https://www.dhs.gov/immigration-statistics/yearbook/2017`. Removals include standard removals, stipulated orders, expedited removals, reinstatement of removal, and administrative removal. Returns include withdrawal of application for admission, voluntary return, and voluntary departure. See Rosenblum et al. (2014) for details on each category of departure.

Figure 4: Mexico to US migration rates



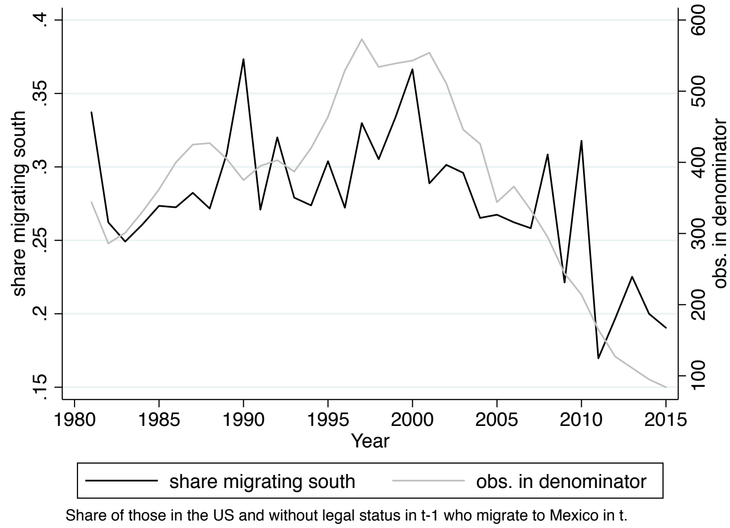
(a) Immigrants Without Legal Status in the U.S.



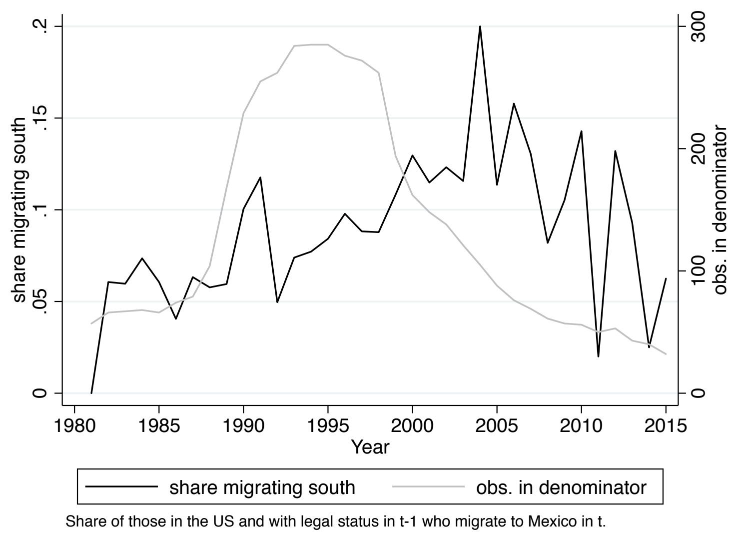
(b) Immigrants With Legal Status in the U.S.

Source: Authors' calculations based on Mexican Migration Project data. See text for sample restrictions. The black line in panel (a) shows the share of those in Mexico and without U.S. legal status in year $t-1$ who migrate to the U.S. in year t, listed on the x-axis, with values plotted on the left axis. Panel (b) shows the share of those in Mexico and with U.S. legal status in year $t-1$ who move to the U.S. in year t. In both panels, the gray line shows the number of observations in the denominator of the relevant share in each year (i.e. those in Mexico and without U.S. legal status in year $t-1$ in panel (a) and those in Mexico and with U.S. legal status in year $t-1$ in panel (b)), plotted on the right axis.

Figure 5: US to Mexico migration rates



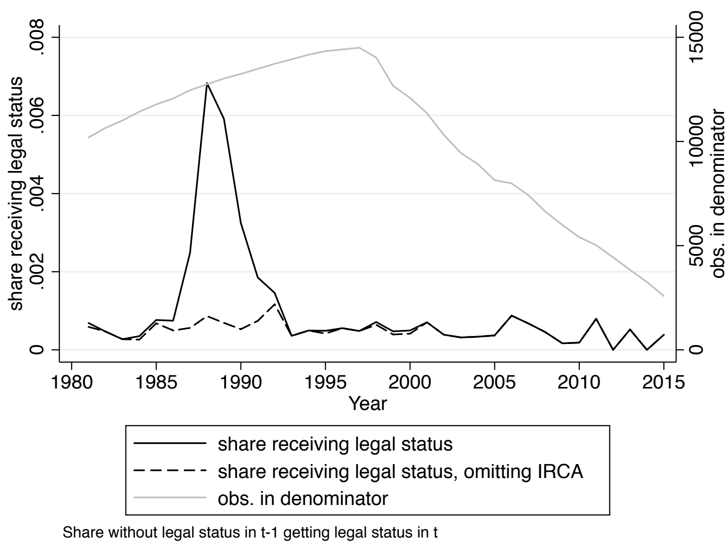
(a) Immigrants Without Legal Status in the U.S.



(b) Immigrants With Legal Status in the U.S.

Source: Authors' calculations based on Mexican Migration Project data. See text for sample restrictions. The black line in panel (a) shows the share of those in the U.S. and without U.S. legal status in year $t-1$ who migrate to Mexico in year t, listed on the x-axis, with values plotted on the left axis. Panel (b) shows the share of those in the U.S. and with U.S. legal status in year $t-1$ who move to Mexico in year t. In both panels, the gray line shows the number of observations in the denominator of the relevant share in each year (i.e. those in the U.S. and without U.S. legal status in year $t-1$ in panel (a) and those in the U.S. and with U.S. legal status in year $t-1$ in panel (b)), plotted on the right axis.

Figure 6: Legal Status Transition Rates



Source: Authors' calculations based on Mexican Migration Project data. See text for sample restrictions. The solid black line shows the share of those without U.S. legal status in year $t-1$ who get legal status in year t. The dashed black line plots the same share, omitting those who report receiving legal status under IRCA. The gray line shows the number of observations in the denominator of the relevant share (i.e. those without U.S. legal status).

Table 1: Summary Statistics.

Panel (a): Characteristics in survey year	
Number of household heads observed	14,676
Share female	0.131
Age distribution	
18-29	0.112
30-39	0.251
40-49	0.277
50-59	0.243
60-65	0.118
Education distribution (years)	
0-2 (low)	0.133
3-11 (middle)	0.674
12+ (high)	0.194
Share in the U.S.	0.052
Share with U.S. legal status	0.028
Panel (b): Migration patterns	
Number of observed Mexico to U.S. migration events	4,694
Distribution of Mexico to U.S. migration events per person	
0	0.810
1	0.127
2	0.038
3+	0.025
Distribution of spell length in the U.S. (years)	
1	0.481
2	0.173
3	0.089
4	0.050
5+	0.207
10+	0.104
20+	0.029

Authors' calculations based on Mexican Migration Project data on household heads. See text for additional sample restrictions. Panel (a) shows the characteristics of the household heads in our sample as observed in the year of the survey (i.e. with one observation for each individual). Panel (b) uses the retrospective panel dimension of the data to measure migration patterns. Note that the distribution of spell lengths includes censored spells at the beginning or end of the panel for each individual.

Table 2: Net utility parameter estimates

Legal Status:	Unauthorized			Authorized		
Education:	Low	Middle	High	Low	Middle	High
Mexico to U.S.	-5.91	-5.33	-6.05	-3.43	-2.68	-0.88
	(0.66)	(0.44)	(2.50)	(0.43)	(0.34)	(6.81)
U.S. to Mexico	-0.096	-0.0021	-0.065	-0.66	-0.97	-4.47
	(0.071)	(0.47)	(2.67)	(0.44)	(0.35)	(7.19)
Stay in U.S.	-0.21	-0.25	-0.17	0.24	0.13	0.002
	(0.049)	(0.032)	(0.17)	(0.040)	(0.024)	(0.37)

These estimated parameters show the net utility from a given migration decision, conditional on education and legal status. The net utility from staying in Mexico is normalized to zero for each group. Standard errors in parentheses.

Table 3: Time effects in utility

1994-2000	-0.0048
	(0.013)
2001-2005	0.00021
	(0.015)
2006-2009	-0.021
	(0.023)
2010-2018	-0.12
	(0.022)

These parameters report the additive increase in utility when living in the U.S. in a given year. The excluded group is years 1980-1993. Standard errors in parentheses.

Table 4: Legal transition rates

Education group	p_t^l
Low	0.00038
	(0.000081)
Middle	0.00054
	(0.000051)
High (12+)	0.00058
	(0.00010)
IRCA (δ)	0.0035
	(0.00025)

We report the probability of being granted legal status in a given period. These depend on education level, and we allow the probability to shift in the years following IRCA (1987-1991).

Table 5: Model fit

		Mexico to U.S.		U.S. to Mexico	
		Data	Model	Data	Model
Education group	Legal status	(1)	(2)	(3)	(4)
Low	Unauthorized	0.79%	0.80%	28.03%	26.86%
Low	Authorized	13.59%	13.94%	7.30%	7.38%
Middle	Unauthorized	1.41%	1.40%	30.82%	30.53%
Middle	Authorized	15.10%	15.27%	11.24%	10.97%
High	Unauthorized	0.79%	0.79%	24.73%	25.04%
High	Authorized	11.22%	9.16%	4.37%	4.58%

Columns (1) and (2) consider people who start a period in Mexico. Column (1) shows the share of people in the relevant group that moves to the U.S. in the MMP data. In column (2) we calculate the model-predicted probability of moving to the U.S. for each individual, and then report the average over the sample. Columns (3) and (4) repeat this for the set of people who start a period in the U.S., looking at the model-predicted and observed rates of return migration.

Table 6: Counterfactuals: Mexico to U.S. migration rates

	Deportation	Legal status	Entry ban	Migration rate	
Row	rate	transition rate	for deported	Never deported	Deported
1	Baseline	Baseline	No	1.08%	1.08%
2	Baseline	Baseline	Yes	1.08%	1.08%
3	10%	Baseline	No	0.91%	0.91%
4	10%	Baseline	Yes	0.91%	0.91%
5	10%	1%	Yes	0.88%	0.91%

We report the model-predicted migration rates. This is for a 33 year old unauthorized immigrant in 2017 with the middle education level. We show these rates for when a person has never been deported, and when they have been deported in prior years.

Table 7: Counterfactuals: Average years in the U.S. as an unauthorized immigrant

	Deportation	Legal status	Entry ban	Years unauthorized
Row	rate	transition rate	for deported	in the U.S.
1	Baseline	Baseline	No	0.33
2	Baseline	Baseline	Yes	0.33
3	10%	Baseline	No	0.21
4	10%	Baseline	Yes	0.21
5	10%	1%	Yes	0.20

Considering only when a person is not able to move to the U.S. legally, we compute the share of years spent in the U.S.. We multiply this by 9 (the average number of years observed in the data) to get the average number of years spent in the U.S. for unauthorized immigrants in each scenario.

Online Appendices

(Not for publication)

A Identification of net utility parameters

We use a 2 period model to show how the net utility parameters are identified. We denote living in Mexico with M or $\ell = 1$, and living in the US with US or $\ell = 2$. We will work backwards, so first consider the period 2 decision. In the data, we see the share of people who make each choice. We denote this as $p^2(\ell_2|\ell_1)$, which is telling us the share of people in the data who choose location ℓ_2 when they start the period in ℓ_1. We see the following information in the data in period 2.

$$\begin{aligned}
p^2(M|M) &= p_{11}^2 \\
p^2(US|M) &= p_{12}^2 = 1 - p_{11}^2 \\
p^2(M|US) &= p_{21}^2 \\
p^2(US|US) &= p_{22}^2 = 1 - p_{21}^2
\end{aligned} \tag{12}$$

Next we can look at the choice probabilities derived from the model We normalize the cost of moving to be 0 when you do not switch locations. Denote $v_t(\ell_t|\ell_{t-1})$ as the deterministic value of living in location ℓ_t when you lived in location ℓ_{t-1} in the previous period. Since period 2 is the terminal period, this just consists of the utility from a choice (as there is no continuation value since we assume $V_{T+1} = 0$). Denote u_1 as the utility from living in Mexico and u_2 as the utility from living in the US. The cost of moving from Mexico to the US is c_1 and the cost of return migration is c_2. Then for the terminal period,

$$\begin{aligned}
v_2(M|M) &= u_1 \\
v_2(US|M) &= u_2 - c_1 \\
v_2(M|US) &= u_1 - c_2 \\
v_2(US|US) &= u_2
\end{aligned} \tag{13}$$

We can rewrite the utility and moving costs in terms of net utilities, defining the $\tilde{u}$ terms as follows

$$\begin{aligned}
\tilde{u}_{11} &= u_1 \\
\tilde{u}_{12} &= u_2 - c_1 \\
\tilde{u}_{21} &= u_1 - c_2 \\
\tilde{u}_{22} &= u_2
\end{aligned} \tag{14}$$

If we can identify the $\tilde{u}$ terms, we can back out the u and c terms.

Since we assumed a discrete choice model with extreme value shocks, the choice probabilities have a logit form. In period 2,

$$p^2(M|M) = \frac{\exp(\tilde{u}_{11})}{\exp(\tilde{u}_{11}) + \exp(\tilde{u}_{12})} \tag{15}$$

We know this moment in the data, so

$$p_{11}^2 = \frac{\exp\left(\tilde{u}_{11}\right)}{\exp\left(\tilde{u}_{11}\right) + \exp\left(\tilde{u}_{12}\right)} \tag{16}$$

We can also calculate the probability that a person moves from Mexico to the US:

$$p^2(US|M) = \frac{\exp\left(\tilde{u}_{12}\right)}{\exp\left(\tilde{u}_{11}\right) + \exp\left(\tilde{u}_{12}\right)} \tag{17}$$

Using the data moment,

$$\begin{aligned}
p_{12}^2 &= \frac{\exp\left(\tilde{u}_{12}\right)}{\exp\left(\tilde{u}_{11}\right) + \exp\left(\tilde{u}_{12}\right)} \\
1 - p_{11}^2 &= \frac{\exp\left(\tilde{u}_{12}\right)}{\exp\left(\tilde{u}_{11}\right) + \exp\left(\tilde{u}_{12}\right)} \\
p_{11}^2 &= \frac{\exp\left(\tilde{u}_{12}\right)}{\exp\left(\tilde{u}_{11}\right) + \exp\left(\tilde{u}_{12}\right)}
\end{aligned} \tag{18}$$

Comparing equations (16) and (18), we see that using both moments p_{11}^2 and p_{12}^2 gives the same equation since they are co-linear, so we have to make a normalizing assumption. We set $\tilde{u}_{11} = 0$. This allows us to identify $\tilde{u}_{12}$ using equation (18).

We can also look at these decisions for people who start the period in Mexico. In this case,

$$\begin{aligned}
p^2(M|US) &= \frac{\exp\left(\tilde{u}_{21}\right)}{\exp\left(\tilde{u}_{21}\right) + \exp\left(\tilde{u}_{22}\right)} \\
p_{21}^2 &= \frac{\exp\left(\tilde{u}_{21}\right)}{\exp\left(\tilde{u}_{21}\right) + \exp\left(\tilde{u}_{22}\right)}
\end{aligned} \tag{19}$$

From the period 2 decision, once we normalize $\tilde{u}_{11} = 0$, we can identify $\tilde{u}_{12}$. We will use the period 1 decision combined with equation (19) to identify the remaining parameters.

We now consider the period 1 decision, and assume that the period 0 location is exogenously given. Denote η as the extreme value shocks, γ as Euler's constant, and β as the discount rate. We can write the value function for a person who starts period 1 living in Mexico as follows

$$\begin{aligned}
V_1(M) &= \max_{\ell=1,2} \tilde{u}_{1\ell} + \eta_\ell + \beta E_1 V_t\left(\ell\right) \\
&= \max_{\ell=1,2} \tilde{u}_{1\ell} + \eta_\ell + \beta \log\left(\exp\left(\tilde{u}_{\ell 1}\right) + \exp\left(\tilde{u}_{\ell 2}\right)\right) + \beta\gamma
\end{aligned} \tag{20}$$

We can use equation (20) to write the log probability that a person who starts the period in Mexico chooses to stay in Mexico

$$\begin{aligned}
\log\left(p_1(M|M)\right) &= \log\left(\exp\left\{\tilde{u}_{11} + \beta \log\left[\exp(\tilde{u}_{11}) + \exp(\tilde{u}_{12})\right] + \beta\gamma\right\}\right) \\
&- \log\left(\exp\left\{\tilde{u}_{11} + \beta \log\left[\exp(\tilde{u}_{11}) + \exp(\tilde{u}_{12})\right] + \beta\gamma\right\}\right. \\
&+ \left.\exp\left\{\tilde{u}_{12} + \beta \log\left[\exp(\tilde{u}_{21}) + \exp(\tilde{u}_{22})\right] + \beta\gamma\right\}\right) \\
&= \log\left(\exp\left\{\beta \log\left[1 + \exp(\tilde{u}_{12})\right]\right\}\right) \\
&- \log\left(\exp\left\{\beta \log\left[1 + \exp(\tilde{u}_{12})\right]\right\} + \exp\left\{\tilde{u}_{12} + \beta \log\left[\exp(\tilde{u}_{21}) + \exp(\tilde{u}_{22})\right]\right\}\right)
\end{aligned} \tag{21}$$

We can now calculate the log odds ratio of staying in Mexico between periods 1 and 2:

$$\begin{aligned}
\log\left(\frac{p_1(M|M)}{p_2(M|M)}\right) &= \log(p_1(M|M)) - \log(p_2(M|M) \\
&= \log\left(\exp\left\{\beta \log\left[1 + \exp(\tilde{u}_{12})\right]\right\}\right) \\
&- \log\left(\exp\left\{\beta \log\left[1 + \exp(\tilde{u}_{12})\right]\right\} + \exp\left\{\tilde{u}_{12} + \beta \log\left[\exp(\tilde{u}_{21}) + \exp(\tilde{u}_{22})\right]\right\}\right) \\
&- \log(\exp(\tilde{u}_{11})) + \log\left[\exp(\tilde{u}_{11}) + \exp(\tilde{u}_{12})\right] \\
&= \log\left(\exp\left\{\beta \log\left[1 + \exp(\tilde{u}_{12})\right]\right\}\right) \\
&- \log\left(\exp\left\{\beta \log\left[1 + \exp(\tilde{u}_{12})\right]\right\} + \exp\left\{\tilde{u}_{12} + \beta \log\left[\exp(\tilde{u}_{21}) + \exp(\tilde{u}_{22})\right]\right\}\right) \\
&+ \log\left[1 + \exp(\tilde{u}_{12})\right] \\
&= (1+\beta)\log\left[1 + \exp(\tilde{u}_{12})\right] \\
&- \log\Big(\exp\left\{\beta \log\left[1 + \exp(\tilde{u}_{12})\right]\right\} + \exp\Big\{\tilde{u}_{12} + \beta \log\left[\exp(\tilde{u}_{21})\right] - \beta \log(p_{21}^2)\Big\}\Big) \\
&= (1+\beta)\log\left[1 + \exp(\tilde{u}_{12})\right] \\
&- \log\Big(\left[1 + \exp(\tilde{u}_{12})\right]^\beta + \exp(\tilde{u}_{12})\exp(\beta\tilde{u}_{21})(p_{21}^2)^{-\beta}\Big)
\end{aligned} \tag{22}$$

Equation (22), combined with equation (19), allows us to identify the remaining 2 parameters. The idea is that the parameter is identified by looking at the ratio of moving today relative to moving tomorrow. In a dynamic model, the decision on whetehr to move each period changes over time, depending on these utility parameters.

B Data

B.1 Migration Data Coverage

Figure B1: Communities surveyed in the MMP

MMP Communities map produced by the MMP and obtained from `https://mmp.opr.princeton.edu/research/maps-en.aspx`. Black dots represent communities available in the current data extract (MMP170) and utilized in this study. Red dots will be available in subsequent data releases.

B.2 Interior Apprehension Rate

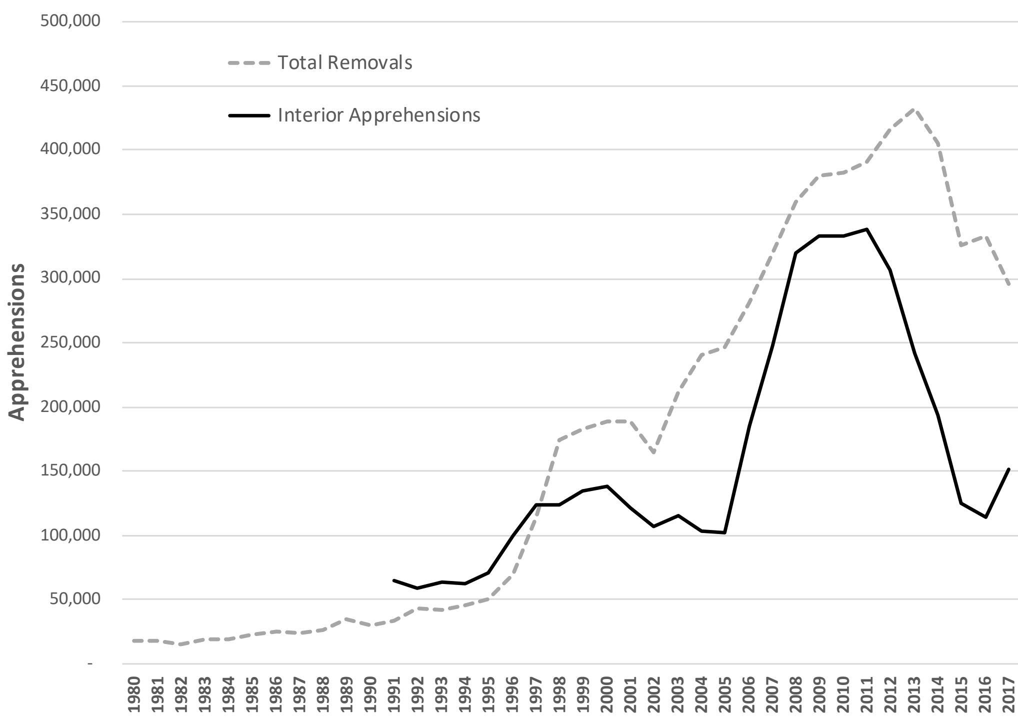
We measure the intensity of interior immigration enforcement as the interior apprehension rate, which we calculate as the yearly number of interior apprehensions divided by the estimated unauthorized immigrant population.

Figure B2 shows a measure of interior immigrant apprehensions covering 1991 to 2017, compiled from Yearbooks of Immigration Statistics, published by the Department of Homeland Security's Office of Immigration Statistics. Interior immigration enforcement responsibility moved from the Immigration and Naturalization Service (INS) to Immigration and Customs Enforcement (ICE) in 2003 with the creation of the Department of Homeland Security. The data therefore aggregate the number of apprehensions falling under relevant INS and ICE programs in each year (see the note for Figure B2 for details). Because this series only extends back to 1991, we additionally plot total yearly removals reported in the 2017 Yearbook of Immigration Statistics. These data cover formal removals both in the interior and at the border, but they nonetheless provide a measure of enforcement intensity in years prior to 1991. In order to construct a consistent series for interior apprehensions throughout our sample period, we proportionally rescale the Total Removals series to coincide with the Interior Apprehensions series in 1991 and use this rescaled measure as a proxy for interior apprehensions for years prior to 1991. The resulting series is shown in Figure B3. This series forms the numerator of our interior apprehension rate measure.

Figure 1 shows two alternative measures of the unauthorized immigrant population of the U.S. We show estimates of the unauthorized population from the Pew Research Center and from official estimates produced by the Immigration and Naturalization Service and the Department of Homeland Security. In both cases, the unauthorized population is estimated using a "residual methodology" in which researchers use estimates of the total foreign-born population of the U.S. and subtract the population of authorized immigrants as measured in administrative data. The total foreign-born population is measured using either the American Community Survey (ACS) or the March Supplement to the Current Population Survey (CPS), with appropriate adjustments for potential undercount of unauthorized immigrants. The population of authorized immigrants comes from administrative data published by the Department of Homeland Security's Office of Immigration Statistics. In spite of slight differences in the samples and various measurement choices, the two data sources provide remarkably similar estimates for the unauthorized population in each year. We therefore focus on the Pew data, since they span our entire sample period. We fill in the missing years by linearly interpolating values based on the adjacent years, with the results shown in Figure B4.

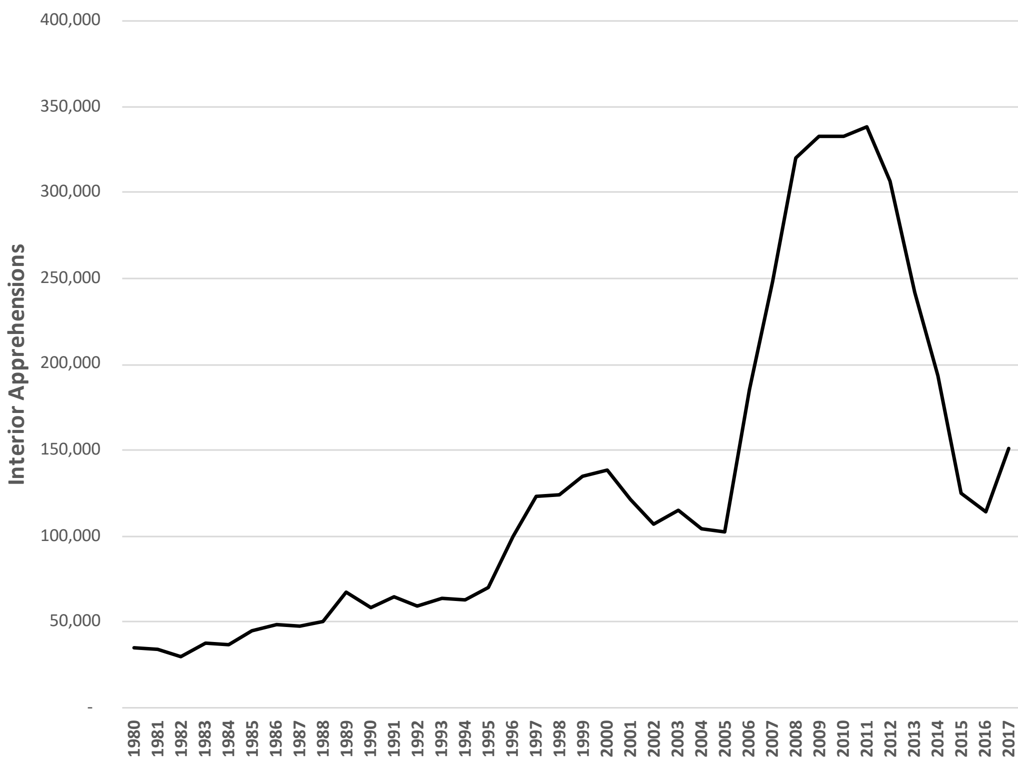
Finally, we combine the series in Figures B3 and B4 to calculate the interior apprehension rate for unauthorized immigrants in each year. The resulting series, appearing in Figure B5, is used to measure the yearly probability of deportation for unauthorized immigrants living in the U.S., as discussed in Section 5.1.

Figure B2: Interior Apprehension Measures



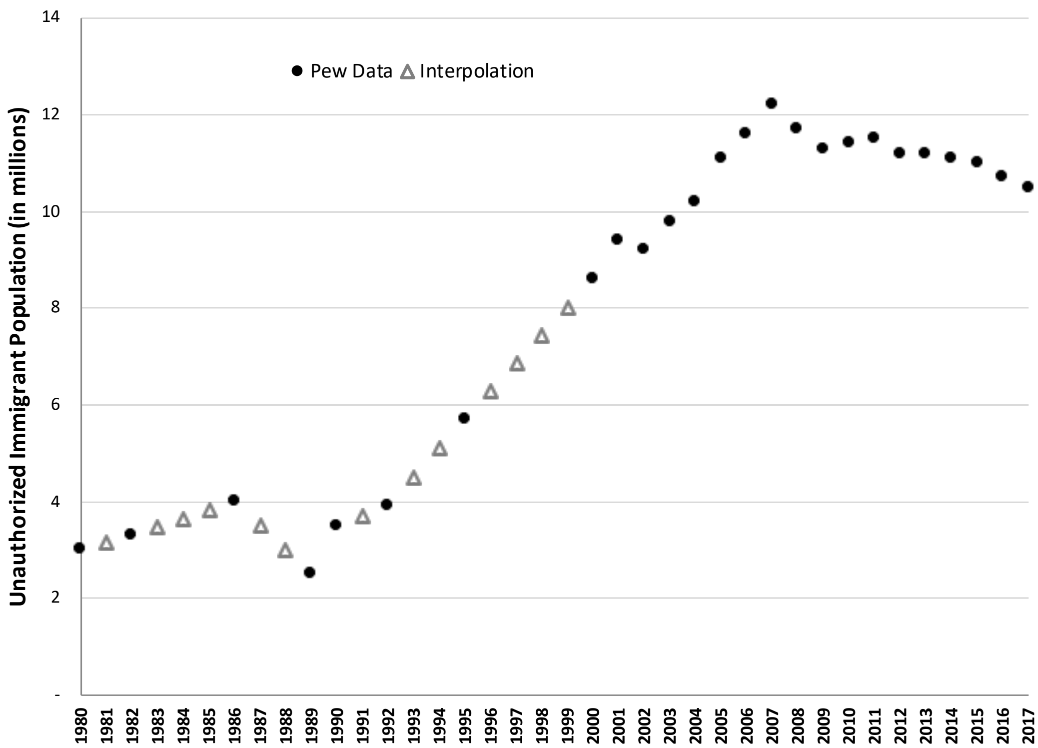
Sources: Interior Apprehensions are measured as follows. For 1991-2005 they reflect apprehensions by the INS Office of Investigations or ICE Homeland Security Investigations. For 2006-2007 they reflect apprehensions by ICE Homeland Security Investigations, Detention and Removal Operations, and the Criminal Alien Program. For 2008-2017 they reflect apprehensions ICE Homeland Security Investigations and Enforcement and Removal Operations. These measures come from various Yearbooks of Immigration Statistics, available at `https://www.dhs.gov/immigration-statistics/yearbook` and the ICE Fiscal Year 2008 Annual Report, available at `https://www.hsdl.org/?abstract&did=35723`. Total Removals reports departures based on a formal order of removal, using data from the 2017 Yearbook of Immigration Statistics. Although these data cover formal removals in the interior and at the border, they provide information on enforcement intensity in years prior to 1991.

Figure B3: Interior Apprehension Series



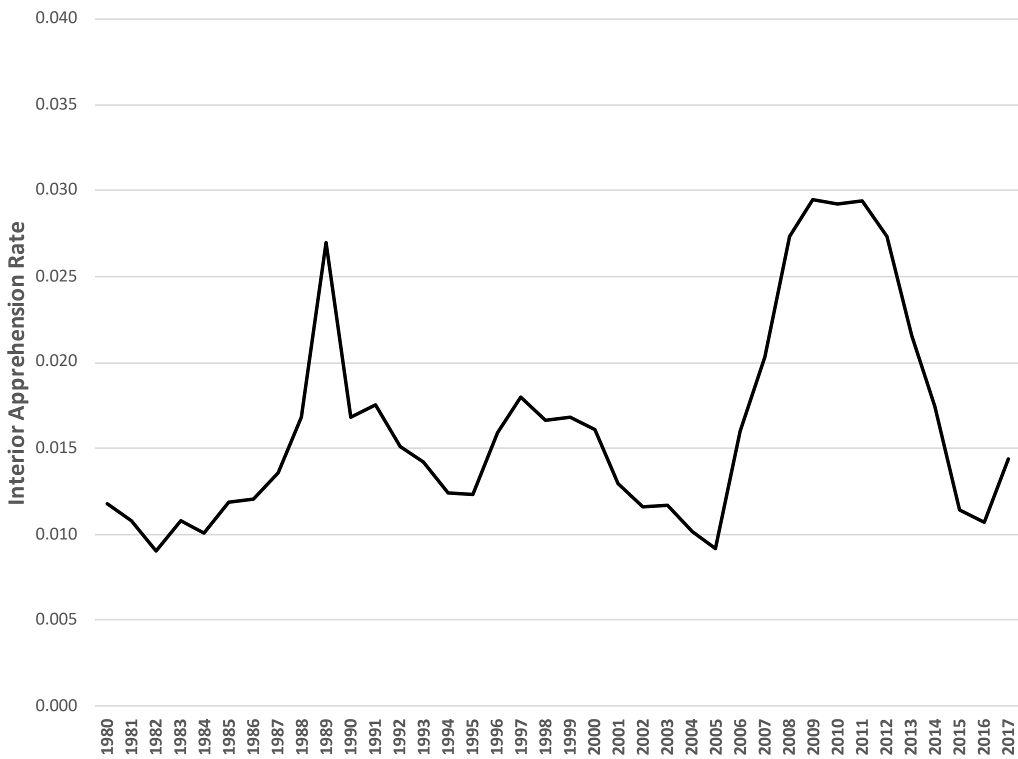
Sources: For 1991-2017, reports the Interior Apprehension measure shown in Figure B2. For 1980-1991, reports a version of the Total Removals series in Figure B2, proportionally rescaled to equal the Interior Apprehension series in 1991.

Figure B4: Unauthorized Immigrant Population Series



Black circles replicate the Pew Research Center series in Figure 1. Hollow triangles show linearly interpolated values filling in the omitted years.

Figure B5: Interior Apprehension Rate



Source: Interior apprehensions from Figure B3 as a share of unauthorized population in Figure B4.