Mexican migration flows and agricultural labor markets in the U.S.

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Abstract

Using information on migratory flows for every Mexican municipality-US county pair throughout the 2006–2019 period, this paper estimates the effect that variations in Mexican migration flows have on U.S. agricultural labor-market outcomes. We instrument for migration-driven changes in local labor supply using a shift-share variable that combines Mexican municipality-level violence rates with preexisting migration network patterns. Our estimates show that, in the short run, decreasing migration rates induce agricultural firms to employ a larger number of indirectly-hired workers, to increase the number of H-2A seasonal worker visas requested, and to pay higher average wages to directly-hired farm workers.

1 Introduction

Relative to population size, immigrant workers play an outsized role in several industries in the U.S. economy. In particular, Mexican-born migrants comprise almost 70% of hired agricultural workers in the United States (Hernandez and Gabbard, 2019). However, migration from Mexico to the United States has steadily declined over the past twenty years, and the U.S. farm labor supply has been contracting for more than a decade. The prevalence of labor shortages in the US agricultural industry is increasing (Zahniser et al., 2018), and the scarcity of available workers has intensified in the last few years (Peri and Zaiour, 2022). A 2019 survey found that 56% of farms in California reported being unable to meet their full labor demand over the previous five years. Common responses to the shortage included raising of wages, adopting labor-saving technologies, and reducing or delaying various cultivation practices.[1] Understanding the relative magnitudes of these response margins, and how short-run responses differ from more structural adjustments in production practices is crucial for the design of better-informed agricultural and migratory policy.

This paper estimates how yearly variations in the number of workers arriving from Mexico to different counties in the United States impact local labor-market conditions in the agricultural industry. To conduct this analysis we instrument immigration flows using a shift-share design that combines information on violence levels in Mexican municipalities with preexisting migration networks as an instrument for variation in the magnitude of migratory flows headed to each U.S. county across time. Using information on migratory flows for every Mexican municipality-US county pair throughout the 2008–2019 period and county-level data on agricultural wages, employment rates, and H-2A visa requests, we are able to quantify how variations in the supply of migrant workers shape agricultural employers' hiring and production decisions.

Our estimates reveal a stark contrast between the short-run and the long-run effects that migratory flows have on agricultural labor markets. In the short run, changes in the stock of available workers lead to a clear substitution pattern in the type of workers hired by agricultural firms. A yearly decrease in the migration rate of Mexican workers arriving to a U.S. county causes a large increase in the number of H-2A seasonal-worker visas requested by agricultural employers, while raising the proportion of workers hired indirectly through crop support firms. We also find that reduced migration flows exert upwards pressure on the average wages of directly-hired farm workers. Our 2SLS estimates indicate that, on average, a 1 standard-deviation decrease in yearly migration rates induces a 0.01% increase in wages paid to directly-hired farm workers, while having no statistically detectable effect on the wages of workers hired indirectly. Conversely, our estimates for the long-run response to migration show that agricultural firms in U.S.

[1] California Farm Bureau Federation. 2019. "Still Searching for Solutions: Adapting to Farm Worker Scarcity Survey".

counties that experienced a larger aggregate migrant-labor supply shock during the 2008–2019 period had *higher* average wage growth by the end of the period, and had larger increases in the proportion of workers hired indirectly through farm-support firms.

The short-run results are consistent with a simple labor-market model in which migrant and incumbent workers are close substitutes. Large yearly inflows of migrants imply an increasing stock of workers and, in general, decreasing recruitment costs and lower average wages. By making available workers more scarce, reductions in migratory flows raise wages and lead employers to seek alternative, potentially more expensive, sources of labor such as indirect hires or the H-2A program. For their part, the long-run results could be explained by a structural model of production that allows for complementarities between capital and labor, and where agricultural firms can eventually adjust their capital-labor ratios and technology choices in the face of changes in the prospects of yearly worker availability (Ottaviano and Peri, 2012; Clemens et al., 2018). At the same time, the tradable nature of agricultural goods might also imply that a higher supply of workers is eventually adjusted for mostly through an expansion in output rather than through wages (Burstein et al., 2020).

The rest of the paper is organized as follows. In Section 2 we present the data, describe the samples and variables used for analysis, and show some general facts about Mexican migratory flows. In Section 3 we motivate the use of our shift-share instrument, and discuss our empirical methodology. Results for our main outcomes are reported in Section 4. Finally, Section 5 concludes.

2 Data and Background

2.1 Mexican migratory flows: the *Matriculas Consulares de Alta Seguridad* data

We measure the yearly inflow of Mexican workers arriving to each U.S. county using information from the *Matrículas Consulares de Alta Seguridad* (MCAS) program maintained by the Mexican government. The MCAS dataset records all *Matrículas Consulares* identification cards issued by Mexican consulates to Mexican-born individuals living in the U.S., and registers both the municipality of origin and the current U.S. county of residence of each cardholder. MCAS are issued to all qualifying Mexican citizens regardless of immigration status or age. While holding a MCAS card does not confer any U.S. immigration status to the person to whom it is issued, many states and local governments allow the document to be used as proof of identity, and so it permits the cardholder to access a services that include opening a bank account, being assigned an Individual Tax Identfication Number (ITIN), or obtaining a driver's license. Since obtaining the MCAS does not entail any additional benefit to authorized migrants, it is generally assumed that MCAS are a measure of

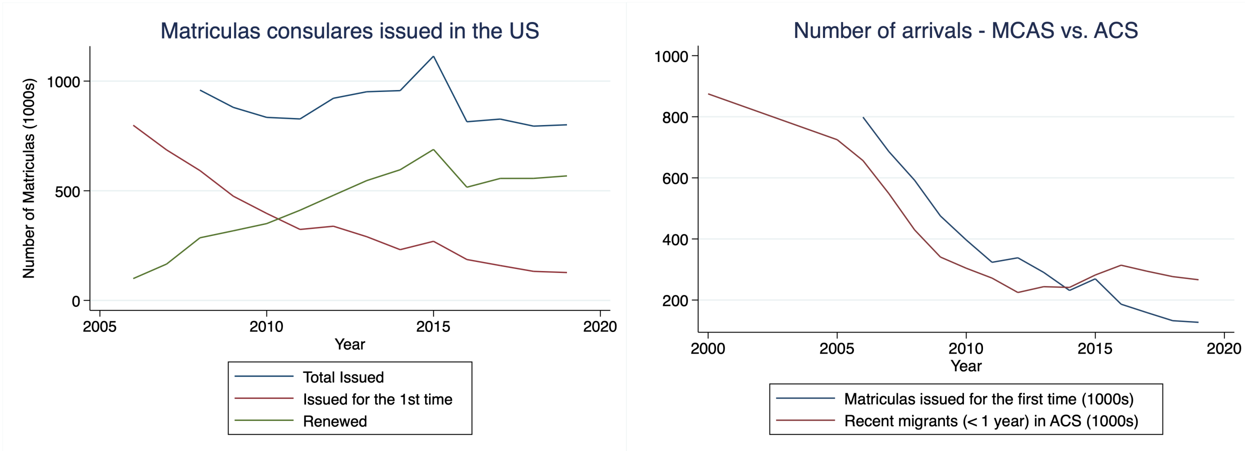

Figure 1: Number of MCAS issued by year. Left panel: Total MCAS issued, renewals, and first-time issuances. Right panel: Number of MCAS issued for the first-time vs. Number of Mexican-born migrants in the ACS with 1 year or less of tenure in the U.S.

unauthorized migration inflows to the U.S. (Massey et al., 2010). Comparing the joint distribution of these inflows both at origin and destination with alternative surveys, Caballero et al. (2018) confirm that MCAS records are in fact a representative and high-quality information source on Mexican migratory flows.

We take yearly MCAS issued for the first time as our main measure of Mexican migration flows to the U.S. from Mexico. Given that MCAS must be renewed every five years it is important, when trying to measure yearly migrant inflows, to separate renewals from first-issuances. The left panel of figure 1 shows the aggregate number of MCAS issued, both for the first time and as renewals, for the 2006–2019 period. While the total number of MCAS issued has remained relatively stable throughout the period, a growing share of this total is due to renewals, while the declining amount of MCAS issued for the first time is consistent with the documented decline in migration inflows throughout this period (Passel and Cohn, 2018). The right panel of the same figure corroborates this fact by documenting the close correspondence between the observed number of MCAS issued for the first time and the number of newly-arrived Mexican migrants to the U.S. as recorded in the *American Community Survey* (ACS).

2.2 Mexican migration networks

We argue that the MCAS records allow us to build a dataset with virtually all undocumented migratory flows for every Mexican municipality-US county pair throughout the 2006–2019 period. The fact that we can observe such finely geographically-dissaggregated data allows us to measure the strength of migratory networks between each origin-destination pair. A large literature (see for example Munshi (2003, 2014)) shows that preexisting migrant community networks at destination are a fundamental determinant of the location choice of future migrants. To compute this network measure we use the first two years in our

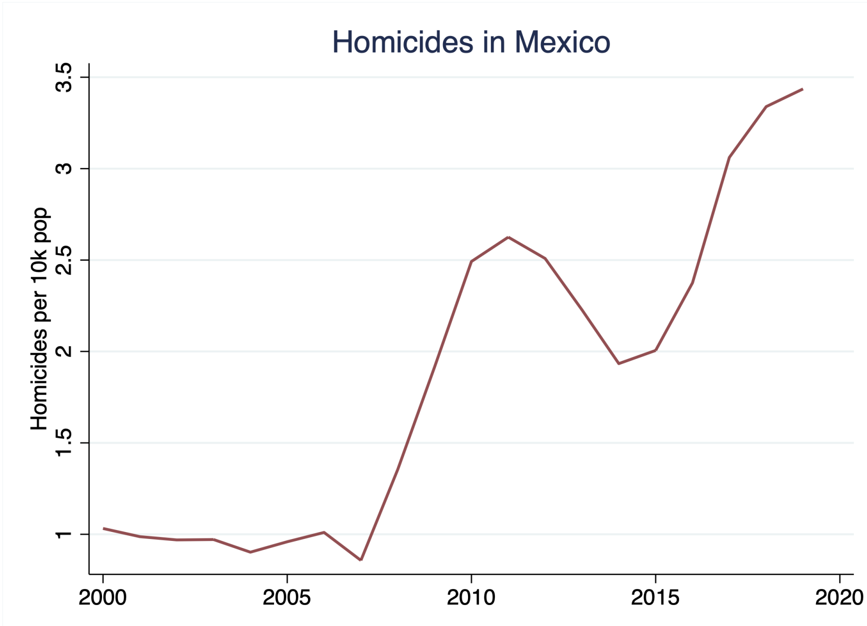

Figure 2: National homicide rates in Mexico 2000-2019. Source: Mexican national statistics institute (INEGI)

data (i.e. 2006 and 2007) and calculate the share of migrants going to each U.S. county out of the total number of migrants leaving each Mexican municipality during this two-year period. As documented by Tian et al. (2022), we find large differences in the historical destination patterns across different Mexican municipalities, even within the same state. We leverage this spatial variation in the settlement patterns of different origin communities to build the shares of our shift-share instrument for migration inflows. The 'shift' part relies on the sharp increase in violence levels of specific Mexican regions starting in 2008 and is discussed below.

2.3 Violence in Mexico

Starting in 2008, Mexico has suffered an unprecedented and drastic increase in violence levels across large parts of its territory. As shown in Figure 2, national homicide rates increased by 300% in 12 years, from 8.6 homicides per 100,000 population in 2007 to 34.4 homicides per 100,000 population in 2019 . While most violence in Mexico is closely related to the illicit drug market supply to the U.S. and the governmental stance on the war on drugs, the specific causes of the sudden surge in homicide rates remain a source of debate (Castillo et al., 2020; Guerrero-Gutiérrez, 2011; Dell, 2015; Williams, 2012). Regardless of their cause, these rapid increases in violence levels across the country have been shown to have negative impacts on labor-market outcomes (Velásquez, 2020), capital accumulation (Brown and Velásquez, 2017), and migration decisions (Orozco-Aleman and Gonzalez-Lozano, 2018).

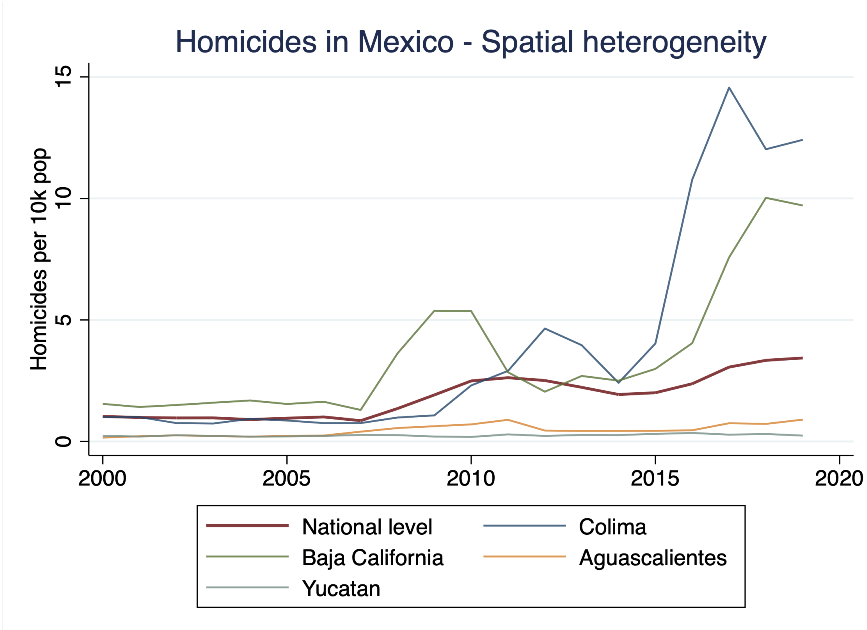

Figure 3: Homicide rates for selected Mexican states. Source: Mexican national statistics institute (INEGI)

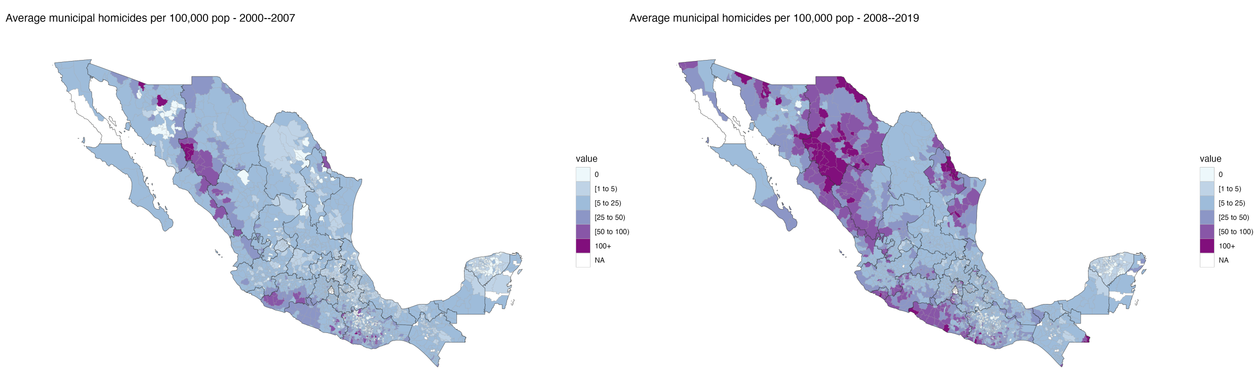

Figure 4: Average yearly homicide rates per 100,000 population. Left panel: 2000–2007. Right panel: 2008–2019. Source: Mexican national statistics institute (INEGI)

We use yearly municipal-level data on violent homicide rates from INEGI, Mexico's national statistical agency. As Figure 3 shows, the growth in violence levels has been heterogeneous across space, with some states suffering a more-than-tenfold increase in murder rates while others showing no increase at all throughout the period. Figure 4 illustrates this spatial heterogeneity at the municipal level. Combining this data with the MCAS information described above, in Section 3 we document the existence of a strong positive correlation between yearly municipal violence levels and migrant outflows to the U.S.. The spatial variation in the increase in violence across the 2008–2019 period acts as the 'shift' component of our shift-share instrument. By combining this component with municipal-county network shares we are able to aggregate destination origin shocks into a yearly destination-level measure of migrant-supply shocks.

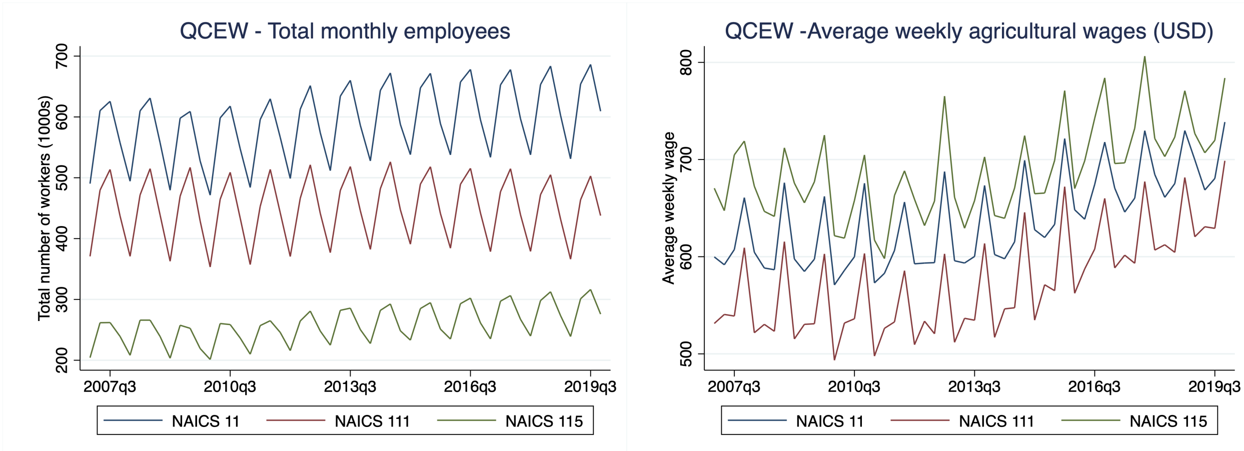

Figure 5: QCEW variables for agricultural workers. Left panel: Number of monthly UI-covered employees. Right panel: Average CPI-deflated weekly wage. NAICS 11: Total agricultural workers. NAICS 111: Crop production. NAICS 115: Agriculture support activities.

2.4 US agricultural wages and employment

To measure labor market outcomes we use county-industry-year level data on wages and employment from the *Quarterly Census of Employment and Wages* (QCEW) program mantained by the U.S. bureau of labor statistics. The QCEW publishes a quarterly count of establishments, employment level, and total wage bill at the 6-digit NAICS industry level for each county in the United States. It is based on the aggregation of all Quarterly Contribution Reports (QCRs) submitted by employers subject to state and federal unemployment insurance laws to each State's accounting system. The QCEW covers more than 95% OF U.S. jobs.

The focus of this paper is on migration's impact on the agricultural sector, and we therefore focus on the quarterly employment levels and wages recorded in the QCEW under NAICS codes 11 (agriculture, forestry, fishing and hunting), 111 (crop production), and 115 (Agriculture and forestry support activities). In order to protect respondent's confidentiality, the published QCEW data suppresses information for industry-quarter-county combinations where the number of establishments is deemed small enough as to make individual information identifiable. This implies that the QCEW is, in practice, an unbalanced panel where industry-specific information for a given county in a given quarter might be missing due to the small number of respondents. In order to avoid selection-bias issues stemming from the unbalanced nature of the panel, for the entirety of our analysis we use only industry-county-quarter combinations that have full information for the entirety of the period. Figure 5 show the national-level trends of employment and wages for the selected industries.

We also estimate the impact of migration on the yearly rates of H-2A workers requested for authorization by agricultural employers in each U.S. county. Data on these requests are publicly available at the individual request level from the Department of Labor. [2] To get yearly county-level requests we aggregate the total unique number of workers certified on each intended worksite according to the stated job start date on each application.[3] Figure 6 shows yearly trends in national H-2A request levels. Since 2008, the number of certified H-2A seasonal workers has more than doubled from under 100,000 workers to nearly 250,000 workers in 2018. By the end of the period this represented nearly 8% of the total amount of workers employed nationally in the agricultural sector. Table 1 shows descriptive statistics for the main variables used in our analysis.

Table 1: County-level summary statistics

	Obs	Mean	Std.Dev.	Min	Max
County Migration per capita	37680	0.0005	0.0010	0.0000	0.0219
County H2A requests per capita	37680	0.0014	0.0068	0.0000	0.2882
NAICS 11: All agricultural workers					
Number of workers per capita	9564	0.0091	0.0166	0.0000	0.1925
Avg. weekly wage (USD)	9564	635.4247	160.5272	257.3249	2072.9571
NAICS 111: Directly-hired agricultural workers					
Number of workers per capita	9564	0.0070	0.0127	0.0000	0.1224
Avg. weekly wage (USD)	9564	575.3454	147.8098	193.8291	3096.8102
NAICS 115: Indirectly-hired agricultural workers					
Number of workers per capita	3180	0.0060	0.0114	0.0000	0.0873
Avg. weekly wage (USD)	3180	674.3216	248.1996	192.8383	2218.9410

Note: Data for U.S. counties pooled across years 2008-2019. Samples for each sub-industry are defined as all counties that, for each NAICS code, have non-missing information in each of the 13 years that comprise the 2007-2019 period. Migration data comes from MCAS records, H-2A figures from the Department of Labor, wage and employment from QCEW.

3 Methodology

3.1 Instrumental variable motivation

Assessing whether changes in migration rates have an effect on wages or employment rates is challenging due to the fact that observed wages and employment are equilibrium outcomes that are endogenous to labor supply, of which migration is but one component. To overcome this challenge we use the interaction of changes in violence levels across Mexican municipalities with observed preexisting migration networks

[2] https://www.dol.gov/agencies/eta/foreign-labor/performance

[3] In some years intended worksites are specified either as cities or zip codes. We harmonize all locations at the U.S. county level using the crosswalks provided by the Missuri Census Data Center https://mcdc.missouri.edu/applications/geocorr2018.html.

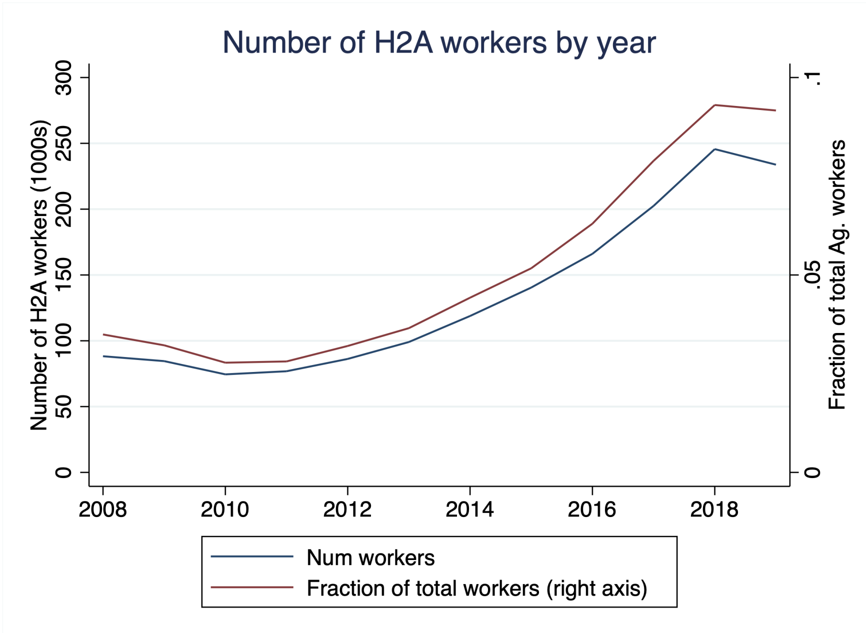

Figure 6: Number of H-2A unique number of workers certified by year and number of agricultural workers at the national level in the ACS.

as an instrument for the number of migrants arriving to each destination county every year. This instrument is based on the observation that variations in the intensity of violence in origin locations are drivers of the decision to migrate, and that the destination choice is further driven by the strength of social networks created by previous migration waves.

To fix ideas, let $M_{c,t}$ be the number of migrants arriving to U.S. county c on year t. (i.e. the number of first-time issued MCAS assigned to county c). Our goal is to find an instrument for the yearly Mexican immigration rate to each U.S. county c:

$$m_{c,t} = \frac{M_{c,t}}{P_{c,t^0}}$$

while the emigration rate leaving to the U.S. from municipality m on year t is

$$n_{m,t} = \frac{M_{m,t}}{P_{m,t^0}}$$

where $P_{m,t}$ and $P_{c,t}$ are, respectively, municipality and county populations at year t and t^0 indicates a year prior to t.[4]

To test the premise that violence levels at origin municipalities are in fact correlated with migratory

[4]In practice, we normalize all of our per capita variables according to the 2005 county and municipality population estimates calculated respectively by the U.S. Census and INEGI.

Table 2: Homicide rates and migration rates - yearly correlation at the Mexican municipality level

	(1) Emigration rate	(2) Emigration rate	(3) Emigration rate	(4) Emigration rate
Homicides per capita	0.9561***	1.2932***	-0.2133	0.2832**
	(0.1759)	(0.1878)	(0.1784)	(0.1376)
Constant	0.0050***	0.0111***	0.0052***	0.0112***
	(0.0001)	(0.0002)	(0.0000)	(0.0002)
Observations	29232	29232	29232	29232
Year FE	No	Yes	No	Yes
Municipality FE	No	No	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the municipality level in parentheses.

outflows we regress yearly municipality-level emigration rates $n_{m,t}$ on yearly homicide rates $V_{m,t} = \frac{\text{Homicides}_{m,t}}{P_{m,t^0}}$

$$n_{m,t} = \alpha + \beta V_{m,t} + \delta_t + \gamma_m + \varepsilon_{m,t} \tag{1}$$

where δ_t and γ_m are respectively year and municipality fixed effects.

Results for regression 1 are shown in table 2. After accounting for both year and municipality fixed effects, our point estimate indicates that, on average, a 10 percentage point increment in the homicide rate is associated with a 2.8 percentage point increase in municipal emigration rates to the U.S.. The magnitude of this correlation is similar to other estimates of the violence-at-origin effect on U.S. migration rates coming from other Central American countries (Clemens, 2021).

While we cannot tell if the observed association of violence and migrant outflows is causal, the existence of this strong correlation is enough motivation to use violence rates as the 'shift' component of our shift-share design. The intuition behind the second part of our instrument is that origin-destination migratory flows can be accurately predicted from aggregate municipality-level outflows multiplied by a measure of the strength of the historical settlement network between each municipality and each U.S. county. More precisely,

$$m_{c,t} = \frac{M_{c,t}}{P_{c,t^0}} = \frac{1}{P_{c,t^0}} \sum_m M_{m,c,t} \approx \frac{1}{P_{c,t^0}} \sum_m \left[M_{m,t} \times \phi^{t^0}_{m,c}\right] = \frac{1}{P_{c,t^0}} \sum_m \left[(n_{m,t} \times P_{m,t^0}) \times \phi^{t^0}_{m,c}\right] \tag{2}$$

where $M_{m,c,t}$ is the migration flow from m to c in t, and the share of total migrants from municipality m that arrived to county c during the 2006–2007 two-year period:

$$\phi^{t^0}_{m,c} \equiv \frac{M_{m,c,t^0}}{\sum_c M_{m,c,t^0}}$$

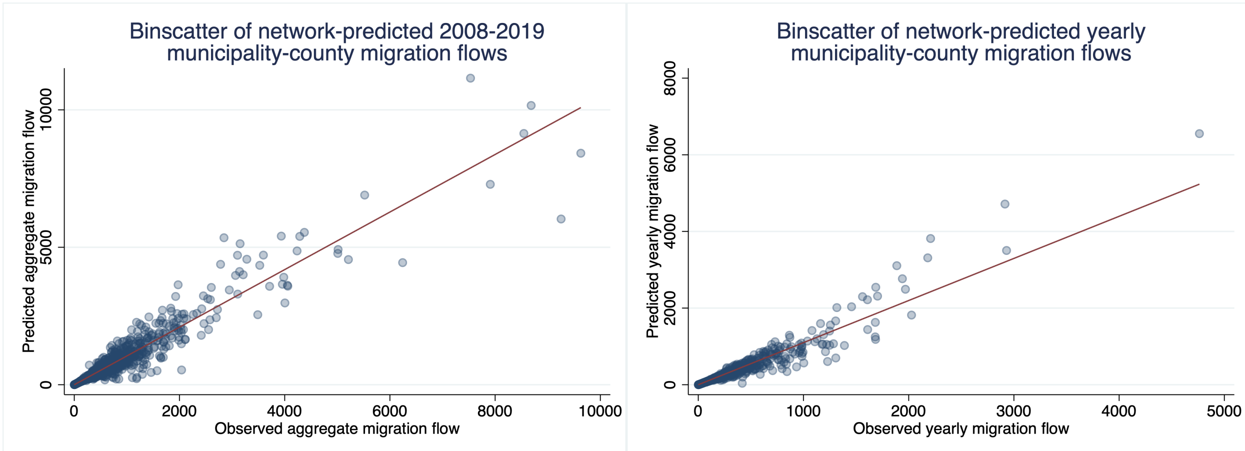

Figure 7: Observed vs. network-predicted migration flows. The left panel shows a binscatter of aggregate (2008-2019) municipality-county observed migration flows and the predicted flow obtained from multiplying total municipality outflows by the network strength measure $\phi^{t^0}_{m,c}$. The right panel shows the same binscatter for yearly municipality-county migration flows.

is our measure of migrant-network strength. Whether this measure is indeed a good predictor of subsequent migrant location decisions can be evaluated in the data: Figure 7 shows that this is indeed the case when using the MCAS data, and that network-predicted migration flows (i.e. $\left[M_{m,t} \times \phi^{t^0}_{m,c}\right]$ in equation 2 are accurate predictors of observed county-municipality migration flows $M_{m,c,t}$.

Leveraging the fact that changes in municipal homicide rates influence emigration intensity, and that historical migration patterns are good predictors of destination choice, we construct the following shift-share instrumental variable:

$$Z^B_{c,t} = \frac{1}{P_{c,t^0}} \sum_m \left[\text{Homicides}_{m,t} \times \phi^{t^0}_{m,c}\right] \tag{3}$$

3.2 First-stage results

To evaluate if the instrument is a strong predictor of county-level migrant inflows we run the following regression:

$$m_{c,t} = \alpha + \delta Z^B_{c,t} + \delta_t + \gamma_c + \varepsilon_{c,t} \tag{4}$$

where δ_t and γ_c are respectively year and county fixed effects. Results for regression equation 4 are shown in table 3. While the simple pooled cross-section comparison of county-year observations shows a strong positive relationship between the instrument and migration rates, once county fixed effects are included and unobserved time-invariant county characteristics are accounted for, this relationship reverses and becomes strongly negative. This is a surprising result and could be subject to a number of different

Table 3: First-stage estimates - County level immigration rates and shift-share instrument

	(1) Migration rate ($m_{c,t}$)	(2) Migration rate ($m_{c,t}$)	(3) Migration rate ($m_{c,t}$)	(4) Migration rate ($m_{c,t}$)
$Z^B_{c,t}$	7.6174***	7.8619***	-5.3182***	-4.2718***
	(0.4627)	(0.4857)	(0.8688)	(0.7744)
Constant	0.0003***	0.0007***	0.0007***	0.0009***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	37680	37680	37680	37680
Year FE	No	Yes	No	Yes
County FE	No	No	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

explanations. Additional estimations in appendix A.1 show that this negative relationship is not due to *i)* The networks component ($\phi^{t^0}_{m,c}$) of the instrument, *ii)* Noisiness of the yearly data, nor *iii)* The aggregation of violence measures across various municipalities.

We interpret the observed results as suggesting that, when comparing across counties, higher average violence levels in the group of municipalities associated to each county are strongly correlated to higher immigration rates, but that this migration tends to happen in relatively less-violent years. That is, while the yearly comparison across counties shows there is a clear positive relationship between violence and migration rates —i.e. counties with stronger connections to more violent municipalities have higher immigration rates— a within-county comparison yields that yearly deviations from county trend in aggregate municipal violence levels is negatively associated to migratory flows when compared to less violent years.

3.3 Empirical Strategy

The specific causal relationship between violence levels and migration rates notwithstanding, the fact remains that our proposed shift-share instrument is a strong predictor of county-level migration flows either doing within-county comparisons or on cross-sectional estimates. We thus follow an instrumental-variable approach to estimate the effect that shocks to the supply of available workers have on U.S. agricultural labor markets.

Our baseline specification is a difference regression of the form

$$\Delta y^i_{c,t} = \beta_0 + \beta_1 m_{c,t} + X'_{c,t}\gamma + \rho_c + \delta_t + e_{c,t} \tag{5}$$

where $\Delta y^i_{c,t}$ is the between-period change in some labor-market outcome, $m_{c,t}$ is the immigration rate (i.e. the change in the stock of workers) in county c at year t, and ρ_c and δ_t are county and year fixed effects. The vector $X'_{c,t}$ includes the state-level minimum wage at year t and a Bartik-style shock that controls for time-varying changes to local labor demand.[5] Equation 5 is estimated with 2SLS using the instrument defined in equation 3. We estimate this regression for yearly intervals as well as for all variables aggregated into 3-year bins as follows:

$$
\begin{aligned}
m_{c,t} &= \frac{\sum_{t-2}^{t} M_{c,t}}{P_{c,t^0}} \\
Z^B_{c,t} &= \frac{1}{P_{c,t^0}} \sum_{t-2}^{t} \sum_{m} \left[\frac{\text{Homicides}_{m,t}}{P_{m,t^0}} \times \phi^{t^0}_{m,c} \right] \\
\Delta y^i_{c,t} &= y^i_{c,t} - y^i_{c,t-2}
\end{aligned}
$$

where $t = \{2010, 2013, 2016, 2019\}$.

To estimate the long-run effect of migration inflows on labor markets we compute the county-level change in outcomes between 2008 and 2019 and regress it on the sum of yearly migration flows for the same period:

$$\Delta y^i_{c,2008-2019} = \beta_0 + \beta_1 m_c + X'_{c,2008-2019} + v_c \tag{6}$$

where $X'_{c,2008-2019}$ controls for minimum-wage growth and long-differences in Bartik-style labor demand shocks. Migration rates are once more instrumented with the sum of the instrument across all periods $Z^B_c = \sum_{t=2008}^{2019} Z^B_{c,t}$. All standard errors are clustered at the county level.

4 Results

4.1 H-2A requests

To evaluate the effect of migration on H-2A request rates we estimate the following version of equation 5:

$$\frac{\text{H-2A}_{c,t}}{Pop_{c,2005}} = \beta_0 + \beta_1 m_{c,t} + X'_{c,t}\gamma + \delta_t + \gamma_c + e_{c,t}$$

Table 4 shows the results of regressing the number of H-2A visa requests per capita on the (instrumented) yearly migration rate to each county. The results show that yearly variations in the rate of Mexican arrivals to a U.S. county are negatively related to the number of H-2A seasonal-worker visas requested by agricultural employers. The population-weighted coefficient indicates that, on average, a 10 percentage point increase

[5] The Bartik shock is computed from the Census *County Business Patterns* (CBP) data. It combines the 2-digit NAICS code industry composition of each county in 2007 with yearly national-level industry growth rates.

in a county's migration rate induces a 1.4 percentage point decrease in the rate of H-2A visa requests.

The magnitude of this substitution rate is large. Using ACS data, Figure 8 in Section **??** shows that, throughout the 2008–2019 period, out of all Mexican migrants that arrived to the U.S. in the previous year, close to 18% found work as agricultural laborers. Hence, the estimated H-2A rate of substitution indicates that for every 18 potential migrants that do not join the agricultural sector any given year, close to 14 additional H-2A requests are made. This back-of-the-envelope calculation suggests that nearly 78% of yearly fluctuations in agricultural labor supply are offset by the H-2A program.

Tables 16 and 17 in Appendix A.2 further show that the strength of this substitution rate increased in the second half of the period studied, and that the bulk of the national-level effect observed is due to counties in the west region of the country, and, to a lesser extent, to counties in the south.

Table 4: Yearly migration flows and H-2A requests

	(1) OLS	(2) 2SLS	(3) OLS - weighted	(4) 2SLS - weighted
Migration rate ($m_{c,t}$)	-0.352***	-0.866***	-0.094*	-0.142**
	(0.122)	(0.206)	(0.049)	(0.067)
Observations	37680	37680	37680	37680
Kleinberg-Paap F		56.03		35.73
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

4.2 Employment rates

To evaluate the effect of migration on employment rates in sub-industry i, we estimate the following version of equation 5:

$$\frac{\Delta \text{Workers}^i_{c,t}}{Pop_{c,2005}} = \beta_0 + \beta_1 m_{c,t} + X'_{c,t}\gamma + \delta_t + \gamma_c + e_{c,t}$$

Tables 5 and 6 show the effect of migration flows on changes in employment rates for, respectively, directly and indirectly hired workers. While OLS estimates suggest that increased migrant flows cause increases in the rate of direct-hires in most quarters, we fail to find compelling evidence of this in the 2SLS estimates. We do find evidence indicating that increased migration rates induce a *reduction* in the number of indirectly-hired agricultural workers. This result is consistent with the presumption that indirectly-hired workers (i.e. workers employed mostly through Farm Labor Contractor (FLC) companies that mobilize crews of workers across larger geographiical areas) are a more expensive, and potentially less efficient way

Table 5: Yearly migration rates and change in employment rate for directly-hired workers (NAICS 111)

	(1) Yr Avg.	(2) Q1	(3) Q2	(4) Q3	(5) Q4
OLS					
Migration rate ($m_{c,t}$)	0.126**	0.107***	0.091*	0.230***	0.071
	(0.051)	(0.034)	(0.052)	(0.082)	(0.068)
Observations	9516	9516	9516	9516	9516
2SLS					
Migration rate ($m_{c,t}$)	0.083	0.157	0.125	-0.004	0.050
	(0.078)	(0.103)	(0.106)	(0.136)	(0.113)
Observations	9516	9516	9516	9516	9516
Kleinberg-Paap F	34.84	34.84	34.84	34.84	34.84
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

Table 6: Yearly migration rates and change in employment rate for indirectly-hired workers (NAICS 115)

	(1) Yr Avg.	(2) Q1	(3) Q2	(4) Q3	(5) Q4
OLS					
Migration rate ($m_{c,t}$)	-0.090	0.042	-0.095	-0.145	-0.162**
	(0.078)	(0.090)	(0.086)	(0.110)	(0.063)
Observations	3156	3156	3156	3156	3156
2SLS					
Migration rate ($m_{c,t}$)	-0.263**	-0.138	-0.188	-0.340	-0.384**
	(0.125)	(0.182)	(0.208)	(0.218)	(0.192)
Observations	3156	3156	3156	3156	3156
Kleinberg-Paap F	13.86	13.86	13.86	13.86	13.86
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

of recruiting workers. Analogous to the H-2A result above, this result suggests that reductions in yearly migration flows shrink the pool of available workers and lead some firms to seek alternative sources of labor. The magnitude of the estimated coefficient indicates that for every 10 percentage point decrease in migration rates there is a 2.6 percentage point increase in the amount of indirectly-hired farm workers.

4.3 Wages

To evaluate the effect of migration on yearly wage-growth in sub-industry i, we estimate the following version of equation 5:

$$\Delta log(\text{wage}^{i}_{c,t}) = \beta_0 + \beta_1 m_{c,t} + X'_{c,t}\gamma + \delta_t + \gamma_c + e_{c,t}$$

Tables 7 and 8 show the effect of migration flows on the growth of wages paid to directly- and indirectly-

Table 7: Yearly migration rates and average wage growth for directly-hired workers (NAICS 111)

	(1) Yr Avg.	(2) Q1	(3) Q2	(4) Q3	(5) Q4
OLS					
Migration rate ($m_{c,t}$)	-4.999***	-3.210*	-5.396***	-5.222***	-4.573***
	(1.211)	(1.770)	(1.413)	(1.294)	(1.750)
Observations	9516	9516	9516	9516	9516
2SLS					
Migration rate ($m_{c,t}$)	-9.633**	-4.583	-0.047	-4.371	-21.814***
	(3.887)	(7.279)	(5.189)	(5.209)	(8.015)
Observations	9516	9516	9516	9516	9516
Kleinberg-Paap F	34.84	34.84	34.84	34.84	34.84
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

Table 8: Yearly migration rates and average wage growth for indirectly-hired workers (NAICS 115)

	(1) Yr Avg.	(2) Q1	(3) Q2	(4) Q3	(5) Q4
OLS					
Migration rate ($m_{c,t}$)	-4.709	-0.994	-4.876	-7.230*	-3.205
	(2.921)	(4.005)	(3.588)	(4.112)	(3.100)
Observations	3156	3156	3156	3156	3156
2SLS					
Migration rate ($m_{c,t}$)	1.332	1.021	-3.258	0.032	8.639
	(6.680)	(10.441)	(10.058)	(10.249)	(9.205)
Observations	3156	3156	3156	3156	3156
Kleinberg-Paap F	13.86	13.86	13.86	13.86	13.86
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the municipality level in parentheses.

hired farm workers. While we fail to find a statistically significant effect on wages for indirect hires, we do find a relatively small negative effect of increased migration rates on average wages paid to directly-hired farm workers. The peak of this effect is concentrated in the fourth quarter of every year, and the magnitude of the effect indicates that, at its fourth-quarter peak, a 1 standard-deviation increase in the migration rate of an average county (i.e., a 0.0013 increase) would induce a drop of 0.028% on average weekly wages paid to directly-hired workers. At the mean weekly wage, this drop would imply an $18 dollar reduction on the average weekly wage. While modest, this observed effect is consistent with the presumption that raising wages is one of the main margins of adjustment farmers employ when faced with a scarcity of workers.

4.4 Long-run results

While the short-run responses to changes in migration flows shown above indicate there is a clear substitution pattern in which lower migration rates lead to more indirect hires, more H-2A requests, and higher wages for directly-hired workers, the estimated long-run responses paint a different picture. Results are shown in tables 9, 10, 11, and 12, and follow the specification defined in equation 6.

In contrast to short-run responses, this long-difference estimates suggest that, in the long run, increased migration rates induce higher average wage growth both for directly and for indirectly-hired workers, with the effect being especially pronounced for the latter. Similarly, the effects on employment rates show that larger migration flows cause a secular increase in the rate of indirectly-hired workers, while having a precisely-estimated null effect on direct-hire employment rates.

Table 9: Long-differences: migration rates and changes in employment rates of directly-hired workers (NAICS 111)

	(1) Yr Avg.	(2) Q1	(3) Q2	(4) Q3	(5) Q4
OLS					
12-year migration rate (m_c)	0.012	0.018	0.020	0.003	0.006
	(0.023)	(0.020)	(0.023)	(0.028)	(0.025)
Observations	793	793	793	793	793
2SLS					
12-year migration rate (m_c)	-0.001	0.001	0.007	-0.007	-0.006
	(0.015)	(0.014)	(0.015)	(0.023)	(0.016)
Observations	793	793	793	793	793
Kleinberg-Paap F	111.56	111.56	111.56	111.56	111.56

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

Table 10: Long-differences: migration rates and changes in employment rates of indirectly-hired workers (NAICS 115)

	(1) Yr Avg.	(2) Q1	(3) Q2	(4) Q3	(5) Q4
OLS					
12-year migration rate (m_c)	0.097**	0.055	0.097*	0.135***	0.102**
	(0.044)	(0.051)	(0.055)	(0.044)	(0.044)
Observations	263	263	263	263	263
2SLS					
12-year migration rate (m_c)	0.090**	0.050	0.102**	0.115***	0.094**
	(0.038)	(0.040)	(0.047)	(0.043)	(0.037)
Observations	263	263	263	263	263
Kleinberg-Paap F	32.81	32.81	32.81	32.81	32.81

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

Table 11: Long-differences: migration rates and wage growth of directly-hired workers (NAICS 111)

	(1) Yr Avg.	(2) Q1	(3) Q2	(4) Q3	(5) Q4
OLS					
12-year migration rate (m_c)	1.754***	0.980**	1.169***	1.614***	2.451***
	(0.350)	(0.399)	(0.386)	(0.379)	(0.509)
Observations	793	793	793	793	793
2SLS					
12-year migration rate (m_c)	1.478***	0.770	0.752	1.555***	2.000***
	(0.411)	(0.480)	(0.476)	(0.450)	(0.602)
Observations	793	793	793	793	793
Kleinberg-Paap F	118.69	118.69	118.69	118.69	118.69

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

Table 12: Long-differences: migration rates and wage growth of indirectly-hired workers (NAICS 115)

	(1) Yr Avg.	(2) Q1	(3) Q2	(4) Q3	(5) Q4
OLS					
12-year migration rate (m_c)	2.299**	1.934*	1.724	2.927***	2.244**
	(0.957)	(1.103)	(1.204)	(0.950)	(1.001)
Observations	263	263	263	263	263
2SLS					
12-year migration rate (m_c)	2.710***	2.407**	2.156*	3.629***	2.371**
	(1.023)	(1.147)	(1.224)	(1.004)	(1.119)
Observations	263	263	263	263	263
Kleinberg-Paap F	34.23	34.23	34.23	34.23	34.23

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

There are several potential explanations for the observed long-run effects of migration on labor markets. One possibility is the existence of distinct types of complementarities between capital and different types of labor and the fact that, with enough time, agricultural firms can eventually adjust their capital-labor ratios and technology choices (Clemens et al., 2018). Alternatively, and given that agriculture produces mainly tradable goods, increases in the relative abundance of labor might cause agricultural firms to make most of the adjustment through an expansion in output rather than through prices, as suggested by Burstein et al. (2020). Finally, an increase in the supply of available labor might spur economic activity in other industries of the economy where a large share of workers are also foreign immigrants (Charlton and Castillo, 2022). This increased competition for workers might lead to faster wage growth and increases in the employment rate of specific types of labor such as FLCs. Disentangling the relative importance of the different mechanisms that might be driving this long-run results seems to us like a natural next step to take.

5 Conclusion

We show how fluctuations in migrant labor supply affect agricultural labor markets and drive changes in farmers' production decisions.

Industry-wide labor shortages and migratory policy are extensively discussed economic issues in current policy debates. This paper contributes to that debate by quantifying the relative importance of the different margins of adjustment through which employers respond to changes in labor supply. By offering estimates on the demand elasticity of agricultural wages in different sub-industries and by documenting how much of the change in agricultural labor supply is offset by H-2A visa approvals, this paper hopes to help inform broader policy questions like the extent to which a tighter labor market will result in the adoption of labor-saving technologies, or whether looser migratory controls could help domestic producers and, through reduction in production costs, improve consumer welfare.

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A Appendix

A.1 Additional First-stage results

To test if the negative relationship between the instrument and migration rates is driven by the 'share' component of the instrument, we define the alternative instrumental variable

$$Z^I_{c,t} = \frac{1}{P_{c,t^0}} \sum_m \left[\text{Homicides}_{m,t} \times \mathbb{1}(\phi^{t^0}_{m,c} > 0)\right]$$

where all (non-zero) origin-destination links are weighted equally. The results of re-estimating regression 4 using $Z^I_{c,t}$ as an instrument are displayed in table 13 and show that the negative sign is still present once county fixed effects are included.

Table 13: First-stage estimates - Instrumental variable without a network component

	(1) Migration rate ($m_{c,t}$)	(2) Migration rate ($m_{c,t}$)	(3) Migration rate ($m_{c,t}$)	(4) Migration rate ($m_{c,t}$)
$Z^I_{c,t}$	0.0041***	0.0043***	-0.0032***	-0.0023***
	(0.0003)	(0.0003)	(0.0005)	(0.0005)
Constant	0.0003***	0.0007***	0.0007***	0.0009***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	37680	37680	37680	37680
Year FE	No	Yes	No	Yes
County FE	No	No	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

It might also be that the negative relationship observed arises because the year-to-year migration measure is too noisy at such a fine temporal disaggregation. This could happen if for a large number of migrants the arrival date into the U.S. and the decision to get a MCAS card are years apart. While the aggregate trends shown in Figure 1 do not seem to suggest this, we nonetheless test this by running an alternative version of regression 4, where both migration rates and the instrument are aggregated into three-year bins. Once again, results for this exercise —shown in table 14— still exhibit the change in sign once county fixed effects are included.

We finally show that the inclusion of unit fixed effects renders the relationship between violence and migration inflows negative even when measured at the origin-destination pair level. Given that the MCAS data allows us to observe the magnitude of all migration flows originating in every Mexican municipality headed to each U.S. county, we are able to run the following regression

$$\frac{M_{c,m,t}}{Pop_{m,t^0}} = \beta_0 + \beta_1 \left[\text{Homicides}_{m,t} \times \phi^{t^0}_{m,c}\right] + \delta_t + \gamma_c + \eta_m + \chi_{c,m} + \varepsilon_{c,m,t} \tag{7}$$

Table 14: First-stage estimates - 3-year bins

	(1) 3-year mig rate	(2) 3-year mig rate	(3) 3-year mig rate	(4) 3-year mig rate
$Z^{B(3year)}_{c,t}$	8.0386***	8.2518***	-7.8713***	-6.4886***
	(0.4726)	(0.4938)	(1.1427)	(1.0508)
Constant	0.0008***	0.0017***	0.0023***	0.0029***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	12568	12568	12568	12568
Year FE	No	Yes	No	Yes
Municipality FE	No	No	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the county level in parentheses.

where $M_{c,m,t}$ is the observed migration from c to m at t, and γ_c, η_m, and $\chi_{c,m}$ are, respectively, county, municipality, and county-by-municipality fixed effects.

Results for regression equation 7 are shown in table 15. These results show that while the separate inclusion of either municipality or county fixed effects does not affect the cross-sectional positive relationship between violence and migration, once municipality-by-county fixed effects are included the relationship once again changes sign and becomes negative.

Table 15: First-stage estimates - Origin-destination level regressions

	(1) $\text{Mig}_{c,m,t}$	(2) $\text{Mig}_{c,m,t}$	(3) $\text{Mig}_{c,m,t}$	(4) $\text{Mig}_{c,m,t}$	(5) $\text{Mig}_{c,m,t}$	(6) $\text{Mig}_{c,m,t}$
$\text{Homicides}_{m,t} \times \phi^{t^0}_{m,c}$	0.645***	0.655***	0.731***	0.226**	0.304**	-0.126*
	(0.238)	(0.243)	(0.267)	(0.111)	(0.137)	(0.070)
Observations	5099796	5099796	5099796	5099796	5099796	5099796
Year FE	No	Yes	Yes	Yes	Yes	Yes
Municip FE	No	No	Yes	No	Yes	No
County FE	No	No	No	Yes	Yes	No
Muni × County FE	No	No	No	No	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the municipality level in parentheses.

A.2 Additional tables and figures

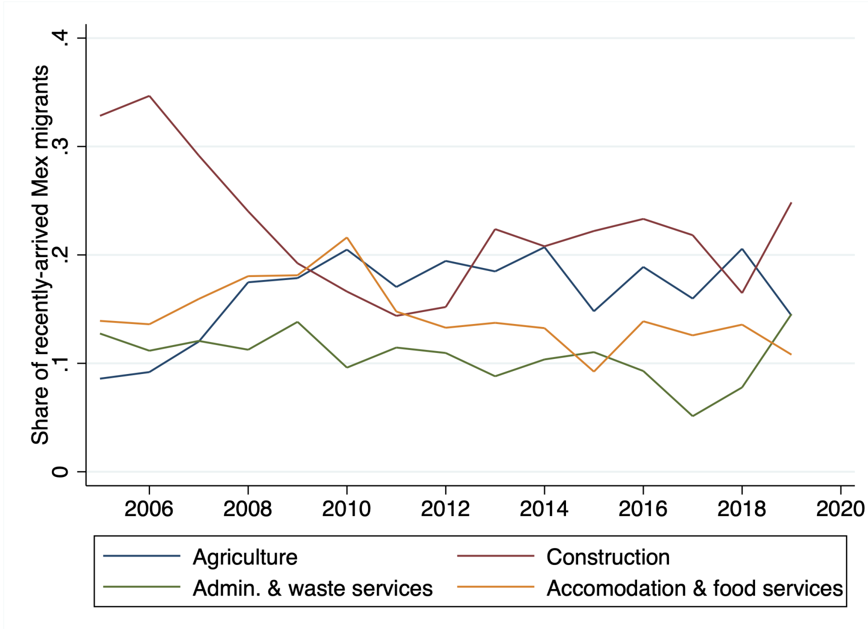

Figure 8: Employment rates by industry for recently arrived (i.e. one year or less) Mexican migrants. Source: ACS

Table 16: H-2A elastcity: 2008-2013 vs 2014-2019

	(1) OLS (2008-2013)	(2) 2SLS (2008-2013)	(3) OLS (2014-2019)	(4) 2SLS (2014-2019)
Migration rate ($m_{c,t}$)	-0.026	-0.529*	-0.616**	-0.728***
	(0.053)	(0.279)	(0.253)	(0.259)
Observations	18750	18750	18750	18750
Kleinberg-Paap F		11.44		347.44
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the municipality level in parentheses.

Table 17: H-2A elastcity by region

	(1) West	(2) South	(3) Northeast	(4) Midwest
OLS				
Migration rate ($m_{c,t}$)	-0.479**	-0.405**	-0.191**	0.160
	(0.243)	(0.169)	(0.080)	(0.138)
Observations	5184	17064	2604	12648
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
2SLS				
Migration rate ($m_{c,t}$)	-1.412***	-0.440	-0.068	0.914
	(0.344)	(0.309)	(0.137)	(0.866)
Observations	5184	17064	2604	12648
Kleinberg-Paap F	21.99	25.69	29.73	2.87
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at the municipality level in parentheses.