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Econ 699

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August 18, 2022

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Mexican Immigration and the Local Average Wage Effect: A Labor Market Analysis.

I. Introduction

Wide-scale immigration is largely influenced by economic motives and political events, where individuals seek to migrate to countries with better wages and standards of living not available in their origin countries. Mass immigration has been proven to improve economic outcomes in destination countries, accelerating industrial growth. The effect of positive economic outcomes from immigration into the U.S. has been studied rather exhaustively, dispelling notions of weakened opportunities and reduced wages for the native-born population. Labor flows from Mexico tend to achieve this effect, as great numbers of less-educated workers enter the U.S. and increase labor force concentration. This paper asks the question: Does Mexican immigration flows significantly affect average earnings (in the origin country)?

Various push-pull factors that can influence local economies in Mexico, however, the prospect of greater freedom and economic opportunity in the U.S. is the largest factor motivating a great proportion of the Mexican population to leave their home country, reducing the labor force and distorting wage levels in the home country.

II. Background

Immigration is a major talking point for politicians and economists, as parties and social groups use the topic to express particular social agendas concerning their welfare and American identity. Interregional dynamics between Mexico and the U.S. has benefited the U.S. economy in various ways, such as enhanced industrial/agricultural efficiency from the outsourcing of labor in

Mexico, trade liberalization resulting in cheaper access to goods, and Mexican migrant stocks raising GDP per capita levels near the southern border. It is unclear how the Mexican economy responds to some of these chain factors, although studies have shown that NAFTA, for example, led to marked increases in returns to education for urban workers (Robertson, 2001) and little to no wage convergence between the U.S. and Mexico (except near the border). A large part of the Mexican economy took a hit shortly after NAFTA's creation - Mexico's estimation of their comparative advantage with the U.S. was overvalued, amidst the likes of China and South Asian countries with high-value low-skilled industries that could produce goods cheaper and more efficiently than Mexico (Hanson, 2003). Nonetheless, Mexico gained manufacturing capability and labor to the disadvantage of the U.S., where U.S. manufacturing jobs were instead outsourced to labor-intensive economies such as China and Mexico.

Political and regional instability engendered a continuing migrant crisis at the border. Cartel violence and rampant poverty, among other destabilizing forces, have pushed swaths of low-skilled laborers into nearby countries, mainly the U.S. at the southern border. While many studies analyze the macroeconomic effects of Mexican crime, the regional repercussions in Mexico have been widely unexamined compared to the current literature studying the residual impact of crime on U.S. natives.

Immigration has a multiregional impact on labor outcomes, productivity, and regional prosperity/poverty. Looking at the economic consequences outside of the U.S. - the top destination country - to countries that comprise a large share of the U.S. migrant stock is warranted. Studying regional trends and macroeconomic conditions in origin countries, like Mexico, can help policymakers envision the future global economy and the direction of the U.S. economy.

III. Literature Review

Immigration literature studies the various interactions among migration patterns, economic policy, and economic outputs, like wage differentials and GDP per capita. The literature develops with changing international migration policy and the expansion of global economies.

I have cited several papers involving the U.S. and the impact of immigration on economic growth. Most of the popular immigration studies involve the U.S. as a destination country for migrants traveling from Central American countries. For this paper, these studies are invaluable for learning about the immigration as a determinant of economic output, given interregional dynamics.

Does Immigration Grease the Wheels of the Labor Market, by George J. Borjas, investigates 1950-1990 Census samples to analyze wage growth and the state of native wages as a byproduct of large-scale immigration. He states that the endogenous clustering of immigrants in high-wage U.S. localities raises the national income level and maximizes the increase in GDP that accrues to natives (Borjas, 2001). Referring to immigrant dispersion, Borjas claims, "natives gain the most when immigrants cluster in one region, regardless of where they cluster, and natives gain the least when immigrants allocate themselves randomly across regions" (Borjas 2001). His main idea *ex post* is that immigration improves labor market efficiency and that push-pull factors predominantly can affect the immigrant minority (particularly less-educated immigrants) as well as the native majority.

Another paper looking at the immigration issue from an American lens is Simpson and Sparber's *The Short- and Long-Run Determinants of Less-Educated Immigrant Flows*. Simpson and Sparber conduct a gravity model for immigration that measures immigrant flows on the macroeconomic covariates of trading countries. The individuals in their sample are in the U.S. labor force and the sample is limited to the years 2000-2009 (Simpson, N. B., & Sparber, C, 2013). In this period, Mexico, India, and the Philippines have the highest shares of less-educated men (in chronological order) immigrating into the U.S. to work in the labor force. 25% of the new immigrants live in the pacific and southeast regions, while 20% live in the Northeast (Simpson, N. B., & Sparber, C, 2013). Their key finding is that fluctuations in GDP significantly affect the movement of less-educated men into the country (Simpson, N. B., & Sparber, C, 2013). Accordingly, women are less responsive than men (less-educated) to short-run GDP fluctuations. Their coefficient results are strikingly indicative of Borjas' claim of immigrant sensitivity to wage differentials, except they evaluate GDP differentials and how immigrant flow responds to that. For example, a $1000 differential in GDP fluctuations between the destination state and origin country leads to a 2.2% immigrant flow (Simpson, N. B., & Sparber, C, 2013). When altering their gravity model to check for robustness, (implementing cluster-robust standard errors) their findings do not change much. Short-run GDP fluctuations continue to be significantly correlated with immigrant flows (Simpson, N. B., & Sparber, C, 2013).

The key similarity between Borjas paper and Simpson and Sparber's paper is that immigrants – leaning towards less-educated, highly mobile migrants - are highly sensitive to bull markets in the U.S. and positive shocks that offer them no choice but to leave their origin countries, especially if those countries are experiencing bad business cycles. Simpson and Sparber acknowledge that "Immigrants might seek employment opportunities in states experiencing growing labor demand that cannot be met by the local native-born labor force" (Simpson, N. B., & Sparber, C, 2013), and Borjas acknowledges this point to some degree. He ultimately thinks that a transfer of immigrants into the U.S. labor market would only create better market outcomes for native born Americans.

The other side of the immigration discussion presents the changing macroeconomic environment in the home country because of citizens leaving their country for opportunities in the U.S. or reform in the home country. Literature on Mexican wage dependence on American FDI as a result of NAFTA (Hanson, 2003) shows that countries can benefit from leveraged economic intervention from the U.S. The literature mentioned previously only glimpsed into the impact of foreign immigration, showing that U.S. regions are greatly benefitted by the presence of foreign laborers. Likewise, the countries comprising most of the foreign population stock in the U.S. (like Mexico) can benefit in similar ways; the comparative advantage Mexico has over the U.S. in low-skilled labor efficiency, for instance, reaps benefits for the Mexican economy as a function of the trading relationship between the two countries.

The creation of maquiladoras in Mexico allowed for greater labor force participation in the interior states, increasing wage growth in these states. The maquiladoras would not have come into existence without the establishment of NAFTA. Hanson (Hanson, 2003) states that migration abroad drives upward pressure on wages in the region from which there is outward migration into the U.S. Hanson (Hanson, 2003) also finds evidence of wage correlations between the U.S. and Mexico, particularly for women. Most notable is that there is economically significant wage growth in areas where there are higher levels of FDIs from the U.S., high levels of exposure to foreign trade, and migration outflows to the U.S. (Hanson, 2003). Regardless of these factors, it seems that the maquiladoras were the deciding factor in igniting unprecedented economic growth in Mexico compared to pre-NAFTA times.

A paper that deals directly with migration flows is *Labor Outflows and Labor Inflows in Puerto Rico* by Borjas, researching specifically how immigration is affecting the home country, in this case Puerto Rico. In short, Borjas (Borjas, 2008) finds that out-migration increases local wages in Puerto Rico through cutting down the labor force. The wage structure in Puerto Rico is not affected significantly by immigration (Borjas, 2008), on the other hand. Meanwhile, U.S. workers possibly experience nominal wage cuts in industries where Puerto Rican inflow is concentrated (Borjas, 2008).

Cartel violence is a major push factor across Mexico that causes families to migrate internally, but also selectively to the U.S. Families forced to abandon their origin states will feel compelled to leave the country for the U.S., as cartels continue to expand their presence throughout the country. Violence caused by the cartels account for trillions of pesos in GDP each year, as drug related violence and gang violence arose greatly during the Calderon presidency that started in 2006 (Cabral, Mollick, & Saucedo, 2016). Corruption within state/local governments make it hard for the federal government to combat the terrorist threat imposed by the various cartel factions. Drug violent crime is predominant in Guanajuato, Jalisco, Chihuahua, and Baja California and has expanded since 2007 to states like Nuevo León and Michoacan (Cabral, Mollick, & Saucedo, 2016).

IV. Data & Preliminary Results

The data is collected mostly from Integrated Public Use Microdata Series International (IPUMS), providing survey and census data for Mexico, and from the Survey on Migration on the Border of Mexico (EMIF), the Mexican survey on migration patterns. Migrant flow data is gathered from the EMIF database, while demographic characteristics and wage data is gathered from IPUMS for the time frame of 2008-2015. The crime data is taken from INEGI, the National Institute of Statistics and Geography, to generate ‘proxy’ variables for Mexican crime. I compress the IPUMS data into annual observations per year for my selected demographic, wage, and control variables. Taking annual state data from 2008-2015, using migrant flow data from the EMIF, we merge the migrant flow data in the IPUMS dataset to get a strongly balanced panel dataset. All 32 Mexican states are sampled for the purpose of the analysis.

Incwage represents monthly income in pesos for wage and salary workers, *popdensity* represents population density in persons per square kilometer of the state, *edyears* represents the maximum years of schooling completed, and *age* indicates the age of the respondent. The share of males in the sample is derived from *sex*. The work experience (*experience*) of laborers is measured by construction of *age*-*edyears*-6. Labor outflow (*outflow*) is indicative of Mexican laborers migrating to the U.S.

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
incwage	30693 50	5348.743	5033.367	1	840031
edyears	30693 50	10.076	5.264	0	18
age	30693 50	35.677	19.984	12	97
popdensity	30693 50	238.231	873.119	8.43	6089.44
labor	256	11898.582	1860.361	6688	17572
lit	30693 50	1.977	.155	1	9
sex	30693 50	1.385	.487	1	2
experience	256	19.653	1.172	16.93	23.55
population	253	3286669.2	2690729.6	575968	16673100

homicides	256	561.984	582.933	28	3903
extortion	230	210	247.806	1	1668
kidnap	240	43.092	50.330	1	262
violentvehic	222	1893.297	4341.142	1	28971
outflow	256	11910.547	14954.013	0	83600
inflow	256	12002.582	13231.851	69	93144

Tabulation of literacy & sex

	Sex		
Literacy	Male	Female	Total
No, illiterate	45648	25466	71114
Yes, literate	1841611	1156531	2998142
Unknown/missing	62	32	94
Total	1887321	1182029	3069350

Outflow as a share of the *population* is taken to construct a net outmigration variable to account for changes in the labor supply due to outmigration. Years of education and experience are expected to be negatively associated with outmigration. We can expect the IPUMS data to be mixed with information from both low-skilled and high-skilled worker populations, leaning towards middle to low-income workers. High-skilled workers possess higher levels of education than low-skilled workers, hence they are 'highly-skilled.' Work experience and years of education are controlled when examining outmigration, specifically net outmigration. Finally, population density accounts for the fact that densely populated regions will process more migrants than less dense regions. Studies on population density and immigration are rare and recent, but evidence on this topic greatly suggests that migration plays a dynamic role in determining population density (Liu & Yamauchi), in fact, urban population dense regions exist largely due to wide scale immigration. It is questionable whether the same population density also produces the outmigration of natives in Mexico, but *popdensity* shows that the population dispersion across Mexico varies a lot by region. The standard deviation for *popdensity* is 873 persons per square kilometer when the average *popdensity* is only 238 persons per square kilometer.

Figure 1 shows the relationship between labor supply and log of average wages –labor supply seems to be positively associated *lincwage* – showing a very weak relationship between labor supply and average wages. Labor supply is not included in the fixed effects model, however, labor supply in conjunction with the regression results for net outmigration shows that Mexican workforce dynamics do not have an isolated effect on individual's wages over time. For the years spanning from 2008-2015: The mean of monthly nominal wage/salary income is $5,348.74 pesos, the average years of school completed is 10, and the average age of the population in Mexico is approximately 36 years of age. Furthermore, an overwhelmingly large proportion of the respondents in the labor survey identified as literate – only 45,648 males and 25,466 females identified as illiterate in total from 2008-2015. The average population density is 238 persons per square kilometer of state – Mexico City unsurprisingly is the most population dense region and Southern Baja California is the least. The wealthiest region in Mexico by GDP per capita is Campeche and the poorest region is Chiapas (OECD, n.d.).

Table 2 shows monthly wage and salary income per state for the seven years of analysis, reflecting a decent representation of regional wealth and well-being. Income shows Southern

Baja California as the richest state, followed by Nuevo Leon and Mexico City (Distrito Federal). Tlaxcala is the poorest state by average monthly wage/income and Campeche is slightly above average for years 2008-2015.

The homicide variable indicates the number of intentional homicides in state i for time t. Summary statistics (

Table 3) show an aggregated average of 562 homicides per year between 2008-2015. The most homicides in a given state for a year in the dataset is 3,903 (Chihuahua) and the least homicides in a given state is 28 (Campeche) (

Table 3). The cross tabulation of statistics shows that, on average, Chihuahua has the highest murder rate among all states at 2,206 homicides per year and that Campeche and Southern Baja California have the lowest murder rate, given 57 homicides per year. Yucatan state also has a very low mean for homicide crime, respectively. The correlation between income and homicide crime is only .1316 (*Table 4*

), however, the preliminary results suggests that the distribution of this type of crime among high income states is relatively low compared to medium to low-income states. More crime can move laborers out of their origin state to other states or the U.S. for better wage opportunities, reducing average income in the origin state if there are not enough employment opportunities.

V. Basic Methodology

The aggregate effect of immigration to the United States on Mexican wages is identified using migrant net outflow share as a main predictor of average wages, controlling for mostly demographic characteristics. Net outmigration is equal to the number of outmigrants minus the number of inmigrants for a particular year. As a share of the total population in which migrants from Mexican states are migrating to the U.S., Migrant net outflow share, then, is equal to net outmigration, divided by the population for that year in state i ((total outmigration for year x – total inmigration for year x) / (population for year x)), estimating the effect of outflows from 2008-2015 on average wage levels across Mexican states. The distribution of wages is left-

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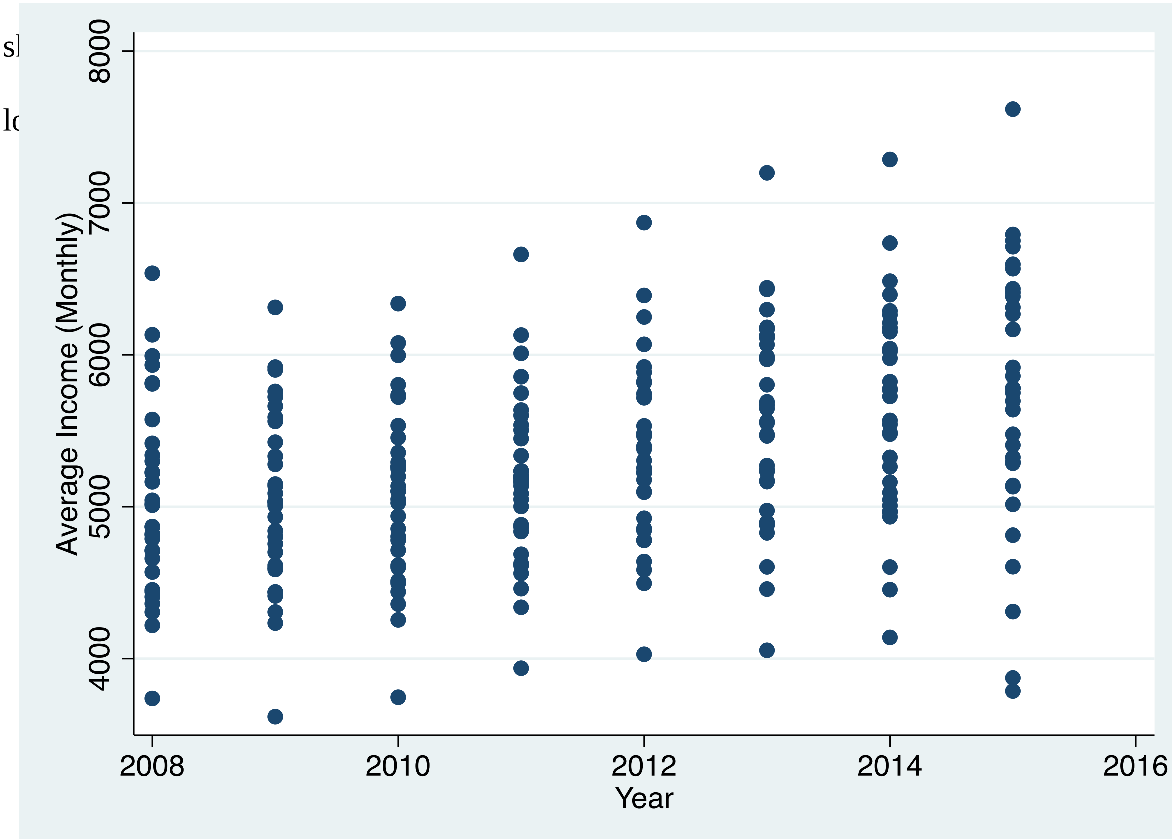

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Net outmigration can be seen as a determinant of local labor market conditions and outcomes, in this case average nominal monthly wages, as outmigration will induce changes in the labor supply (Borjas, 2008). According to the Cobb-Douglas production function, the marginal product of labor eventually decreases due to the law of diminishing returns, keeping capital fixed. In turn, labor productivity declines and wages decrease. Before this change in the labor cycle, wages rise with increasing labor productivity until the marginal product of labor decreases and diminishing rents kick into local firms. If workers migrating to the U.S leads to less workers in Mexican states, then less workers will need more capital-intensive resources or land to raise productivity and keep wages at a high level. Ceteris paribus, net outmigration tends to decrease the number of workers in the origin region, increasing wages as productivity begins to rise again.

The variables in the analysis are consistent with the variables often shown in the immigration economics literature, where we have an outmigration regressor and a set of control variables that control for individual characteristics and are useful for estimating the outmigration variable. *Incwage* represents average monthly income in pesos for wage and salary workers, *maleshare* represents the share of the male population, *edyears* represents average years of education completed, and *experience* represents work experience (*age-edyears-6*) all for state i in time t. Similarly, *outmigration* indicates that a laborer migrated out of state i to the U.S. in time t, representative of net outflow share or net outmigration as a share of the existing population.

Years of education and work experience are reasonable controls in the context of the labor market outcome because workers with higher education and experience levels will be located, on average, in higher wage states. In turn, net outmigration levels are generally lower in these states since the high wages are attracting migrants into the states and discouraging the outflow of laborers to the U.S. There is historical evidence that outmigration to the U.S. from Mexico (but other Central American countries, too, along with Cuba) is substantially comprised of individuals with lower education levels, who can migrate across the border to an accessible U.S. state (mainly California, Texas or Florida) (Borjas, 2001). Relative to Asian and European outmigration, Central/Latin America comprises an overwhelmingly large share of these less-educated migrants (Simpson, N. B., & Sparber, C, 2013).

The gender of the migrant is a crucial aspect among these factors. The vast majority of less-educated migrants outmigrating to the states are male individuals. Hence, including a variable representing the share of the Mexican male labor force is integral to estimating net outmigration. Females are less representative of the entire sample.

If we assume outmigration is related to the labor supply in the labor market, then there will be wage consequences due to migratory fluctuations in Mexican states. The wage elasticity of immigration, then, is an important parameter for the purpose of studying immigration economics. The volume of outmigrants leaving their origin states is relevant to this study, as opposed to qualitative differences between groups, although educational experience is included as a control in the regression. Another way the premise can be framed is asking whether there was enough immigration, or specifically outmigration, between 2008-2015 – a pivotal time for the Mexican economy – to suggest that local workers were getting paid differently due to migrant flow. The partial wage elasticity of outmigration (β_1) measures the relationship between the volume of outmigration and local wages.

Specification (1)

(1) $$\ln incwage_{it} = \beta_1 \, ln \; netoutmigration_{it} + \beta_2 \ln \; maleshare_{it} + \beta_3 \, experience_{it} + \beta_4 \, edyears_{it} + S_i + T_t + \varepsilon_{it}$$

The regression equations use a fixed-effects methodology to estimate the log average wage dependent on migrant flow and the following variables: the share of the male population, the number of years of education completed, and years of experience (represented in the IPUMS sample). The fixed effects equation uses a within estimator to account for state level variation over time. β_1 is the parameter for the log transformed variable for net outmigration, controlling for β_2 - β_4 in state *i* for time *t*; T_t indicates a time fixed effect and S_i indicates a state fixed effect. Specification (2) accounts for heteroskedasticity by implementing cluster standard errors.

The fixed effects regression model is useful in the case of studying net outmigration assuming unobservable characteristics, like cultural attitudes and systemic issues (poverty and corruption) exist in Mexico, which they do. The within estimator (or fixed effects estimator) is derived by demeaning the variables to eliminate the unobservable variation affecting average wage ($y_{it} - \bar{y}_{it}$, $x_{it} - \bar{x}_{it}$; where y = log of average wage and x = log of net outmigration, e.g.). This methodology purposefully adjusts for fixed characteristics, accomplishing one main thing: The observable and unobservable characteristics within the sample are controlled for. Besides poverty, corruption and cultural attributes being obvious state-specific characteristics, the migration cost of outmigration is a time/state characteristic that could covary with one or more of the explanatory variables, especially net outmigration. Essentially, any state-specific characteristics that vary over time that could change the existing migrant share is partialled out.

Theoretically, average wages should increase when net migrant flow is negative, i.e., labor outflows exceed labor inflows (Borjas, 2008). Average wage as a function of labor outflow can expect to deviate, then, depending on the influx of migrants relative to the outflow of migrants seeking labor opportunities elsewhere. My hypothesis is that average wages will respond positively to net outflow to a slight degree, and I expect the effect to be positive. The EMIF data is suggestive to this hypothesis because the net migrant flow is marginally positive, implying that the rate of outflows to inflows is roughly balanced, oddly enough.

Cluster standard errors are used to account for possible heteroskedasticity. Heteroskedasticity is very possibly present, given that wages are taken from different Mexican states. Cluster standard errors account for heterogeneity across states in time t. Specifications (2),(3a),(3b), (2c), (4c) and (2d) implement cluster standard errors.

As a check for heteroskedasticity, we use a Modified Wald test for specification (1) and (2a) and found that the hypothesis for variance across groups being homoscedastic was rejected for both fixed effects equations. The Modified Wald test confirms that there could be heteroskedasticity within certain key state entities. [See

Figure 2:

VI. Instrumental Methodology

A relevant and major impactor of labor productivity in Mexico is crime. When instrumenting crime in the regression, the purpose is to further resolve omitted variable bias and introduce something exogenous and relevant in the regression to discover a particular causal effect Instrumenting crime rates per 100,000 inhabitants for net outmigration can hopefully reduce the endogeneity bias present in the original specification. We expect crime to be a decent instrument assuming it is not directly related to local wages and is causally related to net outmigration and can affect wages through the endogenous variable, outflow. Conceptually, the question is whether crime affects migrant flow but not wages by itself, i.e., are crime variables relevant for net outmigration and do they fit the exclusion restriction (crime is not causally and directly related to wage levels)?

There are several concerns for using crime as an instrument. What if crime in certain Mexican states is directly related to local wage levels? There are a few possibilities here: Organized crime can increase income inequality (individuals in the cartel or connected will be better off than those who are not) if certain states are almost entirely controlled by the cartels, in this case, migration might not even be an economic factor if people are not allowed or discouraged to leave their home states due to the threat of violence or extortion; the effect of crime on the government can change the wage level (Cabral, 2016, p. 3), especially if organized crime penetrates certain labor markets and industries which the cartels control or have a vested interest in; corruption and extortion might affect local wages more than migratory forces. It is not possible to identify a precise causal pathway between crime and economic output, however, the crime conditions in dangerous states/localities motivates families to move abroad. Hence, a proportion of individuals in the labor market decide to migrate elsewhere because of factors like the number of homicides in their home states, regardless of whether the effect of crime is more direct.

Outflow and homicide crime is positively related, as the covariance and correlation coefficient between the two are positive (cov(log *outflow*, log *crime)* > 0 and r > 0). Since crime is a push factor for outmigration, more of the population will leave their origin regions if crime levels increase or threaten the economic stability of the region. Net outmigration is instrumented, first, by taking the natural logs of the homicides per 100,000 inhabitants. Then, violent vehicular robberies (*lviolentvehic*), extortion and kidnappings in rate per 100,000 inhabitants is added to the homicide instrument in subsequent specifications.

The instrumental variable method in this context, still using fixed effects is shown as:

(2a) Specification (2a)

$\ln incwage_{it} = \beta_1 Z_{it} + \beta_2 \, ln \, maleshare_{\,it} + \beta_3 \; experience_{it} + \beta_4 \, edyears_{it} + S_i + T_t + \varepsilon_{it}$

where Z_{it} = ln *homicide*.

Specification (2a) is derived from the 2-SLS technique, the first stage (specification 1a) being: (1a)

$\ln (netoutmigration)_{it} = \delta \, x_{it} + \beta_i x_{it} + \varepsilon_{it}$, where $\delta \, x_{it}$= crime variable and $\beta \, x_{it}$ = control parameters (β_2-β_4).

and the second stage becomes specification (4):

$\ln incwage_{it} = \beta_0 + \beta_1 \, ln \, netoutm\widehat{igra}tion_{it} + \beta_2 \, ln \, maleshare_{\,it} + \beta_3 \, experience_{it} + \beta_4 \, edyears_{it} + S_i + T_t + \varepsilon_{it}$

where $Z_{it} = ln \, netoutm\widehat{igra}tion.$

Specification 2a instruments the natural log of homicides per 100,000 inhabitants across Mexican regions. Specification 2b expands the crime methodology, where Z_{it} = ln *homicides, ln vehic, ln extort* and *ln kidnap* as instruments for ln *netoutmigration* [Similarly, $\delta \, x_{it}$ = crime parameters in the first stage regression].

VII. Independent Lag Variable Model (Net Outmigration)

On further inspection of (1), we realize that exogenous characteristics might be correlated between periods in the case of Mexican net outmigration. Average wages in the current period might be a function of net outmigration in the past year, violating the strict exogeneity condition ('anything that causes the unobservables at time t to be correlated with any of the explanatory variables in any time period' violates the condition) (Woolridge, 2013). We incorporate lag for net outmigration in the fixed effects model to account for this possibility.

Specification (1c) (1c)

$$\ln incwage_{it} = \beta_1 \ln netoutmigration_{it-1} + \beta_2 \ln\ maleshare_{it} + \beta_3\ experience_{it} + \beta_4\ edyears_{it} + S_i + T_t + \varepsilon_{it}$$

β_1 is a lag variable for net outmigration, where last year's migration to the U.S. affects this year's wages. Doing the same alteration for (2b) yields:

Specification (3c) (3c)

$$\ln incwage_{it} = \beta_1\ ln\ netoutm\widehat{\imath gr}at\imath on_{\imath t-1} + \beta_2\ ln\ maleshare\ _{it} + \beta_3\ experience_{it} + \beta_4\ edyears_{it} + S_i + T_t + \varepsilon_{it}$$

except $ln\ netoutm\widehat{\imath gr}at\imath on_{\imath t-1}$ is instrumented for all crime parameters, instead of only homicides.

Introducing explanatory lag in each model can also serve as a check for government policy and crime factors that have a lagged effect on wages in the current period. A government policy limiting the number of visas, for example, can take time to have an impact on migration volume, steadily (but not immediately) increasing labor force participation rates. The Migration Law of 2011 decriminalized illegal immigration into Mexico; this was enacted largely in response to cited hypocrisy by U.S. government officials (illegal migrants can get due process in the U.S. but not Mexico) (González-Murphy, 2011). More comprehensive immigration laws can affect net outmigration, in theory.

We can assume that Mexican outmigration does not instantaneously result in changes to the composition of wages, or the growth of monthly wages. Incorporating feedback by adding a lag variable for net outmigration, then, can be helpful when analyzing the dependent variable. The restrictions of the fixed effects technique can understate the impact of the lagged variable, and since the models are not over specified (there are not a lot of explanatory variables) we only include this model with the lag component as a robustness check.

More than one lag variable would be unnecessary as multicollinearity issues could arise. For this reason, the net outmigration variable by itself is also excluded from the model. Additional lag regressors would remove degrees of freedom from the model, given the insufficient number of observations in the sample for including a larger specification.

VIII. Results

The results for specification (1) are reported in *Table 5*. State-level fixed effects and time fixed-effects are used, adjusting for characteristics within states that do not change over time and are unobservable determinants on individuals' income (monthly wage). Net outmigration has a very small, negative effect on wages over time. Hence, a 1% increase in net outmigration leads to a -.003% decrease in nominal average monthly wages. The result is insignificant at all practical significance levels (*p-value* <0.1, *p-value*<0.05, *p-value*<0.01).

The only significant outcome on *lincwage* in the FE specification came from *experience*, where a year's increase in work experience leads to a -1.67% decrease in average monthly wage (1) *Experience* is not statistically significant anymore at the 5%

significance level when crime is instrumented for net outmigration in *Table 6* (2a). Returns to experience is usually a valuable part of labor market analysis, as more experience is meaningfully correlated with higher wages. The negative impact of crime associated with a change in net outmigration at the state level could lessen the importance of experience in the labor market, where the individual's wage level is not associated with work experience. Negative coefficient estimates are abundant in the results, suggesting that the labor force could suffer productivity losses as a consequence of productive workers leaving the origin regions. The cohort of low skilled workers in the sample also seem to bias the estimates downward, where higher levels of experience do not relate to higher wages.

When instrumenting l*homicides* on *loutmigration*, net outmigration has a positive 0.043% impact on average nominal wages and remains insignificant (*Table 6*). The p-value is greatly lower than the original p-value, so although the crime variable captures much more significance for net outmigration, the model is showing that the variable itself is still insignificant. The sign of *experience* also changes. Assuming Cov $(Z,X_i) \neq 0$, i.e., there is a covariate relationship between homicide crime and net outmigration, the crime variable should at least be a relevant instrument when thinking about migratory pressures and that effect on economic livelihoods. However, the *loutmigration* variable regressed on *lhomicides* does not yield a covariate relationship (1a)

If Z_1 is biased towards zero, the assumption is violated, and crime is not a good instrument for net outmigration. Since *lhomicide* in the first stage and *loutmigration* in the second stage is not practically significant, the instrument is showing great weakness. The joint test of significance yields a F-statistic lower than 10 in each first stage regression, reflecting indication of instrument weakness as well.

Net outmigration is overidentified by the crime instruments (*M*>*K)* in specification (2b) We assume that at least one instrument is exogenous. Sargan's test of overidentifying restrictions yields:

Sargan-Hansen statistic = 2**.868** | Chi^2(3) | P-value = **0.4124**

The null hypothesis cannot be rejected, so the overidentifying restrictions are valid, implying that the additional crime variables are exogenous. The expansion of instruments yields a loutmigration result of -.009, and the sign of the coefficient reverts itself. Again, the instrumental model is biasing the fixed effects estimates and we cannot conclude that crime factors are either a push or pull factor, given that the crime variables are not sufficiently valid instruments.

IX. Robustness Check

A sensitivity analysis consisting of an independent lag variable for net outmigration, the introduction of state GDP in the models, and a check of the original model removing state fixed effects can examine the robustness of the estimates. State GDP can account for regional differences, including state prosperity and overall labor demand. Incorporating state fixed effects presented interpretational challenges in the results; labor market outcomes are influenced by at least several factors we try to control for in the models, and not necessarily governmental influence by the state.

Table 7 shows that in specification (1c) the lag variable for net outmigration shows a negative association between net outmigration and the nominal average wage. An increase in net outmigration from a past year contributes to a much smaller change in the average wage in the current period than shown in original model. The effect is negative and highly insignificant. The instrumental lag variable for violent crime, kidnappings and extortion is showing that a 1% increase in net outmigration from a past year contributes to a -0.018% change in the average wage in the current period (`3c`) On average, this lag model's results are not different from the results derived in *Table 5* and *Table 6*.

Table 8 shows that removing state fixed effects alters the results considerably (`1d`). Now, net outmigration has a very small, positive effect on wages over time and the effect of experience is positive, showing a 4.46% effect on the average wage. The estimates are larger than the original models, and the effects show positive, albeit small effects. Time fixed effects, here, is absorbing the constant time attributes and varying state level attributes that would otherwise affect the relationship between net outmigration and average wages. Not adjusting for state level differences by only including year fixed effects, the coefficient on *loutmigration* becomes positive, signaling that net outmigration does not negatively affect the average wage level over time when state level differences are not adjusted for (migrant outflows are quite variant across states).

We introduce state GDP variation in (

———————————————————————————————————

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Table 9

Specification (1e) is derived from the original FE model, specification (2e) is the instrumental model with crime as an instrument, and specification (3e) is the instrumental model with multiple crime parameters for net outmigration. Introduction of state GDP into the immigration equations (with state and time fixed effects) does not alter the outcomes from the original models. To summarize the model analysis, we show the time variables for year fixed effects. There is highly significant variation in 2012, 2013, 2014 and 2015 in specification (1e) from the base year. Specification (3e) shows highly significant variation in years 2013, 2014, and 2015 from the base year.

X. Conclusion, constraints & future recommendations

The empirical analysis of immigration on local wages/salaries examined whether net outmigration causally impacts wage levels and if crime had an impact on the local labor market outcome through influencing outmigration. We conclude that net outmigration has a negligible effect on local wages in Mexico, and the size and direction of the effect is unclear. Wage levels were not responsive to migration flows in this analysis, as the effect of net outmigration on average wage did not practically change despite several alterations in the fixed effects model.

When net outmigration was controlled with a crime instrument for homicides, the sign of the net outmigration coefficient did change, showing a positive wage elasticity impact. There was another change after expanding the instrumental model, where the estimate of *loutmigration* decreased by .05%, showing downward bias in net outmigration. The hypothesis that crime would be an impactful instrument on migrant outflow was refuted, as the instrument turned out to be weak and largely insignificant. It can be said that ‘a highly statistically significant mouse is not very interesting, and a statistically insignificant elephant is very interesting' (McCloskey, 1996). In the case of the crime variable, neither of these instances are relevant.

The crime variables likely suffered from attenuation bias given the untimely period of the analysis and sampling error due to the relatively limited sample size. Also, including both state and time fixed effects reduces the variation in outmigration as a share of the population, while controlling the other variables. The risk inherent in the methodology is that the variation in net outmigration can be greatly reduced when accounting for various external factors in the models. Alternative research on this topic could reverse the equations from the methodology, mainly addressing the concern of simultaneity. The crime models addressed endogeneity in terms of omitted variable bias (for crime), but simultaneity was not explored. It would not be surprising if future research found that the average wage has a noticeable effect on outmigration, here, as wage levels tend to attract migrants, even less-educated ones.

The models lacked explanatory power from the absence of a large sample size. A larger sample size containing units of explanatory data at the monthly or quarterly level would naturally yield a larger sum of squares and add more state-to-state variation in the models, likely contributing to smaller p-values. The different modelling frameworks used in this study perhaps show how migration flows can cancel out a sizeable effect of the labor market impact. Put differently, in-migrants can be perfect labor substitutes for recent outmigrants in the home country, keeping wage levels constant.

Lagged net outmigration could question whether changes in migration policy or policies affecting the flow of labor do indeed affect the flow of labor to and from Mexico. The basic time lag model from specification (1c) would only suggest that the Calderon administration did not significantly affect the demand for labor in the labor market through such policies insofar as the local wage levels are dependent on migrant flow as a determinant for labor demand. The time lag model has one lag, however, and there is no policy variable included in the specification so the overall governmental policy effect on this analysis is speculative and inconclusive.

Future papers should continue research on this topic by estimating wage differentials between U.S. localities outmigrants are gravitating to and their home states, and by examining the migratory patterns of certain workers, specifically high-skilled and low-skilled. Net in-migration is a driver of net outmigration, so the semantics of the immigration terminology should also be carefully considered. Much work has been done on labor market effects on immigration, but much work remains to be done on establishing the relationship between immigration and labor market outcomes, or the lack thereof. The research on this relationship can grow if the data on immigration becomes more transparent and more published to the public.

XI. Appendix

Descriptive Statistics

Table 1

Summary statistics: Population Density by State

State	Mean	SD	Min	Max
Aguascalientes	220.632	7.904	206.72	233.39
Baja California	45.817	1.721	42.85	48.73
Baja California Sur	9.669	.748	8.43	10.93
Campeche	15.528	.601	14.48	16.51
Coahuila de Zaragoza	19.063	.588	18.07	20.04
Colima	117.997	5.626	108.39	127.21
Chiapas	69.07	2.192	65.29	72.72
Chihuahua	14.679	.366	13.96	15.28
Distrito Federal	6039.268	23.438	5987.95	6089.44

Durango	13.995	.388	13.44	14.7
Guanajuato	186.71	4.152	179.25	193.42
Guerrero	55.501	.949	53.56	56.95
Hidalgo	134.248	4.375	126.49	141.36
Jalisco	97.772	3.024	92.37	102.65
M√©xico	720.577	28.041	674.8	769.15
Michoac√°n de Ocampo	77.229	1.538	74.31	79.69
Morelos	380.926	11.339	361.78	399.97
Nayarit	41.448	1.981	38.05	44.7
Nuevo Le√≥n	76.558	2.775	71.94	81.28
Oaxaca	42.095	.714	40.78	43.26
Puebla	175.831	4.514	168.2	183.18
Quer√©taro	163.529	6.405	152.73	174.38
Quintana Roo	33.112	2.416	29.41	37.13
San Luis Potos√≠	44.091	1.092	42.1	45.91
Sinaloa	52.704	1.237	50.41	54.66
Sonora	15.766	.59	14.72	16.77
Tabasco	94.893	2.43	90.91	98.62
Tamaulipas	44.175	1.339	41.76	46.46
Tlaxcala	308.489	10.912	290.09	326.61
Veracruz de Ignaci~e	111.187	2.25	107.3	114.7
Yucat√°n	51.759	1.621	49.13	54.42
Zacatecas	20.603	.449	19.85	21.31

Note – Density represents persons per square kilometer

Table 2

Summary statistics: Wage & Salary Income

State	Mean	SD	Min	Max
Aguascalientes	4828.085	3795.914	43	100000
Baja California	5899.393	4787.356	45	400000
Baja California Sur	6850.202	6410.488	80	594000
Campeche	5631.182	5579.205	6	230000
Coahuila de Zaragoza	5720.039	5167.192	21	200000
Colima	5518.559	4441.993	17	130000

Chiapas	4954.263	5077.322	50	801000
Chihuahua	5817.297	7095.751	10	516000
Distrito Federal	6181.086	6881.214	86	740112
Durango	4764.816	3592.369	30	80000
Guanajuato	4749.679	3385.889	12	90000
Guerrero	4521.602	3922.973	30	450000
Hidalgo	5391.633	5414.783	4	500003
Jalisco	5412.57	4155.158	1	129000
M√©xico	4912.579	4945.57	65	740240
Michoac√°n de Ocampo	5182.795	4209.443	43	140000
Morelos	4397.076	3635.114	50	107500
Nayarit	5401.665	4251.442	15	160000
Nuevo Le√≥n	6214.417	5341.35	1	166088
Oaxaca	5102.515	4293.355	21	220000
Puebla	4655.974	5502.085	1	674051
Quer√©taro	5386.998	4222.761	50	240000
Quintana Roo	5973.652	5082.756	50	270600
San Luis Potos√≠	5110.261	4994.526	40	280000
Sinaloa	5765.584	5005.5	41	250000
Sonora	5973.041	5423.22	86	510320
Tabasco	6041.472	5867.574	15	365502
Tamaulipas	5428.424	5183.049	50	258000
Tlaxcala	3952.948	3338.867	16	225750
Veracruz de Ignaci~e	5148.345	4941.757	16	387067
Yucat√°n	4760.131	5122.632	30	600000
Zacatecas	5197.403	6655.91	30	840031

Note – (Monthly) Wage is reported in pesos

Table 3

Summary of Crime (Homicides)

State	Mean	SD	Min	Max
Aguascalientes	55.125	15.634	38	74
Baja California	758.625	98.43	590	884
Baja California Sur	57.125	40.442	28	151

Campeche	57.25	10.223	41	69
Chiapas	492.25	89.728	326	613
Chihuahua	2205.625	1072.8	945	3903
Coahuila	448.25	217.934	179	771
Colima	134.375	81.995	33	287
Distrito Federal	772.625	43.922	713	854
Durango	599.375	285.967	238	1024
Guanajuato	589	206.504	257	879
Guerrero	1745.875	466.386	951	2310
Hildalgo	126.375	20.528	83	143
Jalisco	918.875	276.764	462	1222
Mexico	1674.625	398.248	1153	2130
Michoacan	758.125	113.518	565	904
Morelos	497.125	216.174	135	862
Nayarit	213.25	132.912	83	456
NuevoLeon	810	618.569	263	2003
Oaxaca	649	101.985	472	752
Puebla	462.625	95.062	338	619
Queretaro	96	27.182	58	139
Quintana Roo	217	24.769	172	269
San Luis Potosi	290.25	99.628	158	417
Sinaloa	1181.75	299.058	846	1714
Sonora	521.625	78.016	393	654
Tabasco	154.375	36.099	117	233
Tamaulipas	616.75	255.137	288	1015
Tlaxcala	57.25	10.525	42	71
Veracruz	645	228.971	347	968
Yucatan	41.875	6.534	33	53
Zacatecas	136.125	57.64	74	235

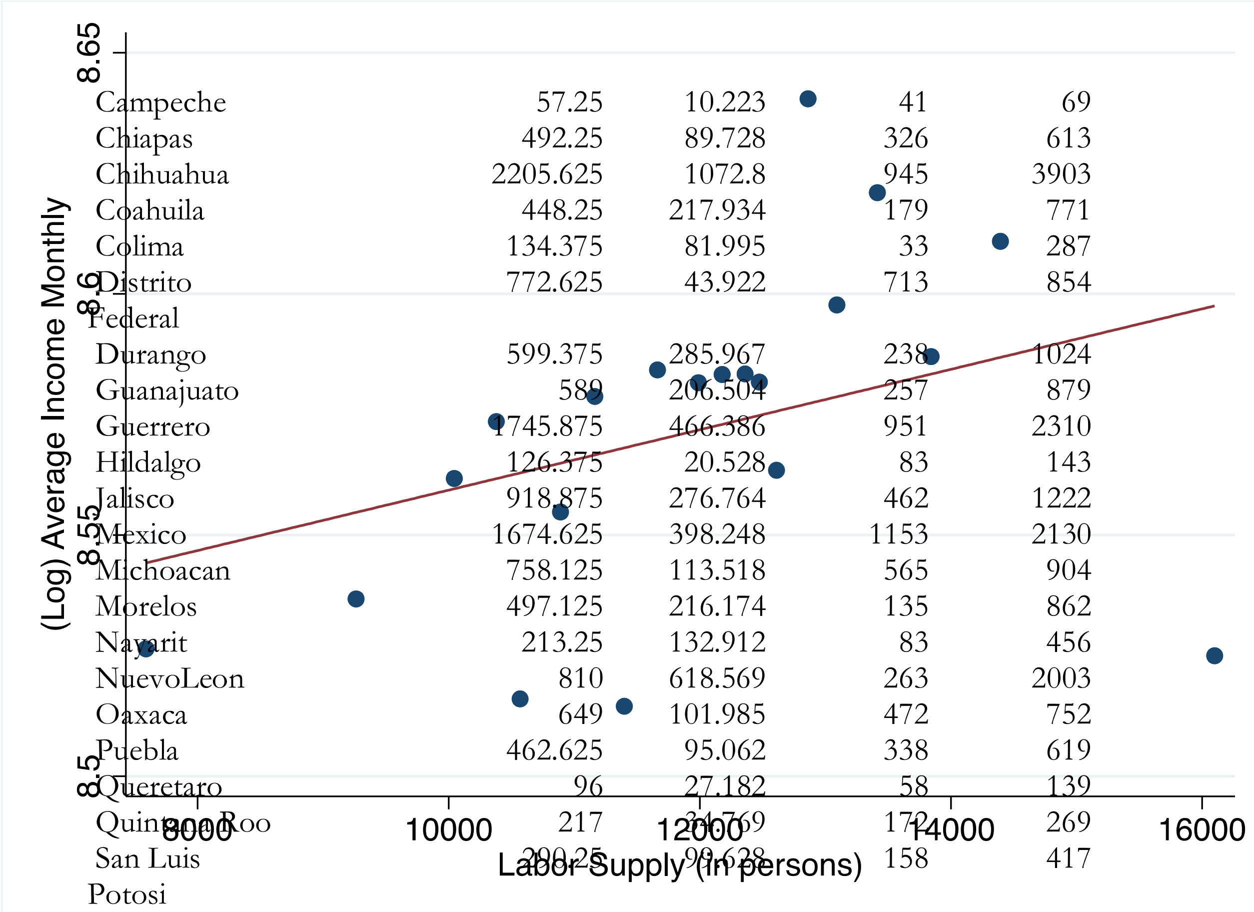


Figure 1

Log of Average Wage as a function of the Labor Supply

Correlation coefficient between Log of Average Wage and Log of Homicides

Table 4

Variables		
lincwage	1.000	
lhomicides	0.1316	1.000

Fixed Effects Model Specifications:

Determination of Net Outmigration, 2008-2015

Table 5

Dependent Variable: lincwage		
RHS	(1) FE	(2) FE(VCE)
loutmigration	-0.00269 (0.358)	-0.00269 (0.407)

experience	-0.0167*	-0.0167
	(0.031)	(0.099)
edyears	-0.0122	-0.0122
	(0.192)	(0.133)
lmaleshare	-0.0627	-0.0627
	(0.519)	(0.426)
_cons	9.203***	9.203***
	(0.000)	(0.000)
F-statistic	50.52	119.86
R-sq	0.833	0.833
adj. R-sq	0.750	0.817

Note: Right hand side (RHS) variables listed in the left column. P-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001. Observations include 32 Mexican states and 7 years of analysis; N=256. F-statistic for joint significance is reported.

Figure 2:

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: residuals are homoscedastic Ha: residuals are not homoscedastic (groupwise heteroskedasticity)

chi^2 (30) = 9.2×10^{27}
Prob>chi^2 = 0.0000

Figure 3:

Modified Wald test for groupwise heteroskedasticity in IV fixed effect regression model

H0: residuals are homoscedastic Ha: residuals are not homoscedastic (groupwise heteroskedasticity)

chi^2(8) = 4.1×10^{27}

<u>Prob>chi^2</u> =   0.0000

Instrumental Variable Determination of Net Outmigration

Table 6

Dependent Variables: loutmigration (1a), lincwage (2a,3a)

RHS	(1a) First Stage FE	(2a) Second Stage FE	(3a) Second Stage FE(VCE)
lhomicides	-0.292		
	(0.436)		
experience	0.158	-0.0167	-0.0167
	(0.592)	(0.057)	(0.063)
edyears	0.200	-0.0179	-0.0179*
	(0.584)	(0.118)	(0.048)
lmaleshare	7.282*	-0.330	-0.330
	(0.049)	(0.189)	(0.125)
loutmigrat~t		0.0431	0.0431
		(0.171)	(0.137)
_cons	-39.18*	10.62***	10.62***
	(0.025)	(0.000)	(0.000)
F-Statistic	4.91	26.96	32.81
R-sq	0.383	0.582	0.582
adj. R-sq	0.079	0.500	0.563

Note – Right hand side (RHS) variables listed in the left column. P-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001. Observations include 32 Mexican states and 7 years of analysis; N=256. F-statistic for joint significance is reported.

IV Determination of Net Outmigration: IV Expansion

Dependent Variable: loutmigration (1b), lincwage (2b,3b)

RHS	(1b) First Stage FE	(2b) Second Stage FE	(3b) Second Stage FE(VCE)
lhomicides	-0.827		
	(0.130)		
lextort	-0.243		
	(0.320)		
lkidnap	0.0388		
	(0.853)		
lvehic	-0.0663		
	(0.781)		
experience	0.214	-0.0132	-0.0132
	(0.544)	(0.123)	(0.111)
edyears	0.192	-0.00380	-0.00380
	(0.663)	(0.726)	(0.616)
lmaleshare	5.500	-0.00744	-0.00744
	(0.241)	(0.957)	(0.947)
loutmigrat~n		-0.00921	-0.00921
		(0.462)	(0.365)
_cons	-29.20	8.799***	8.799***
	(0.161)	(0.000)	(0.000)
F-statistic	3.39	18.15	26.71
R-sq	0.454	0.814	0.814
adj. R-sq	0.062		

Note – Right hand side (RHS) variables listed in the left column. P-values in parentheses. * p<0.05, ** p<0.01, *** p<0.001. F-statistic for joint significance is reported.
Crime variables are missing some state data. Campeche, Colima and Puebla are states with missing observations for extortion/vehicular robberies per 100,000 inhabitants; N=196.

Robustness Checks:

Lagged Net Outmigration and the Average Wage Effect

Table 7

Dependent Variable: lincwage

RHS	(1c) FE	(2c) FE(VCE)	(3c) IV	(4c) IV(VCE)
loutmigrat~1	-0.000718	-0.000718	-0.0178	-0.0178
	(0.860)	(0.865)	(0.485)	(0.541)
experience	-0.0102	-0.0102	-0.00858	-0.00858
	(0.323)	(0.075)	(0.356)	(0.184)
edyears	-0.0236	-0.0236	-0.00587	-0.00587
	(0.125)	(0.069)	(0.679)	(0.597)
lmaleshare	0.000223	0.000223	-0.0414	-0.0414
	(0.999)	(0.998)	(0.752)	(0.676)
_cons	8.945***	8.945***	8.796***	8.796***
	(0.000)	(0.000)	(0.000)	(0.000)
F-statistic	26.96	32.81	18.31	30.92
R-sq	0.700	0.700	0.8200	0.8200
adj. R-sq	0.555	0.672		

Note – Right hand side (RHS) variables listed in the left column. P-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001. Observations include 32 Mexican states and 7 years of analysis; N=256. (9-10) F-statistic for joint significance is reported.

Crime variables are missing some state data. Campeche, Colima and Puebla are states with missing observations for extortion/vehicular robberies per 100,000 inhabitants; N=196. (11-12)

Determination of Net Outmigration, 2008-2015: Time Fixed Effects

Table 8

Dependent variable: lincwage

RHS	(1d) FE		(2d) FE(VCE)
loutmigrat~n	0.00130	loutmigrat~n	0.00130
	(0.869)		(0.831)
edyears	0.0253	edyears	0.0253
			(0.091)
		experience	0.0446***
			(0.001)
		lmaleshare	0.389
			(0.326)

	(0.210)
experience	0.0446***
	(0.000)
lmaleshare	0.389
	(0.198)
_cons	5.857***
	(0.000)
F-statistic	7.33
N	119
R-sq	0.213
adj. R-sq	0.141

Note – Right hand side (RHS) variables listed in the left column. P-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001. Observations include 32 Mexican states and 7 years of analysis; N=256. F-statistic for joint significance is reported.

Table 9

Dependent variable: lincwage

RHS	(1e) FE	(2e) IV	(3e) IV 2
loutmigrat~n	-0.00161	0.0186	-0.00860
	(0.604)	(0.623)	(0.450)
experience	-0.0171*	-0.0216	-0.0142
	(0.032)	(0.097)	(0.139)
edyears	-0.0130	-0.0167	-0.00535
	(0.188)	(0.244)	(0.657)
lmaleshare	-0.0913	-0.230	-0.0299
	(0.371)	(0.426)	(0.840)
lstateGDP	-0.230**	-0.279	-0.225
	(0.010)	(0.052)	(0.134)
2009.year	-0.00644	-0.00253	-0.0144
	(0.509)	(0.861)	(0.238)
2010.year	0.0227*	0.0319	0.0156
	(0.022)	(0.132)	(0.228)

2012.year	0.0883***	0.133	0.0682
	(0.000)	(0.120)	(0.056)
2013.year	0.143***	0.177**	0.123***
	(0.000)	(0.009)	(0.000)
2014.year	0.171***	0.210**	0.150***
	(0.000)	(0.006)	(0.000)
2015.year	0.233***	0.284**	0.204***
	(0.000)	(0.004)	(0.000)
_cons	12.19***	13.60***	11.71***
	(0.000)	(0.000)	(0.000)
F-statistic	33.85	21.33	13.36
R-sq	0.851	0.754	0.825
adj. R-sq	0.767		

Note – Right hand side (RHS) variables listed in the left column. P-values in parentheses: * p<0.05, ** p<0.01, *** p<0.001. Observations include 32 Mexican states and 7 years of analysis; N=256. (15) F-statistic for joint significance is reported.

IV is the original IV model and IV 2 is the IV model with the expansion of instruments for net outmigration. Crime variables are missing some state data. Campeche, Colima and Puebla are states with missing observations for extortion/vehicular robberies per 100,000 inhabitants; N=196. (17)

Overview of Fixed Effects Regression Models

Table 10

Fixed Effects Model from Specification 1

lincwage	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
loutmigration	-.003	.003	-0.93	.358	-.008	.003	
experience	-.017	.008	-2.20	.031	-.032	-.002	**
edyears	-.012	.009	-1.32	.192	-.031	.006	
lmaleshare	-.063	.097	-0.65	.519	-.256	.13	
Constant	9.203	.46	20.02	0	8.288	10.118	***

Mean dependent var	8.571	SD dependent var	0.132
R-squared	0.833	Number of obs	119
F-test	39.336	Prob > F	0.000
Akaike crit. (AIC)	-550.710	Bayesian crit. (BIC)	-520.140

**** p<.01, ** p<.05, * p<.1*

Table 11

Instrumental Variable Model from Specification 7

lincwage	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
loutmigrationhat	-.009	.013	-0.74	.462	-.034	.015	
edyears	-.004	.011	-0.35	.726	-.025	.017	
experience	-.013	.009	-1.54	.123	-.03	.004	
lmaleshare	-.007	.139	-0.05	.957	-.279	.265	
Constant	8.799	.661	13.31	0	7.503	10.095	***

Mean dependent var	8.580	SD dependent var	0.116
Overall r-squared	0.184	Number of obs	92
Chi-square	9335791.271	Prob > chi2	0.000
R-squared within	0.814	R-squared between	0.063

Year-to-year Variation in Crime Rate per 100,000 people, 2008-2015

Average & Deviation

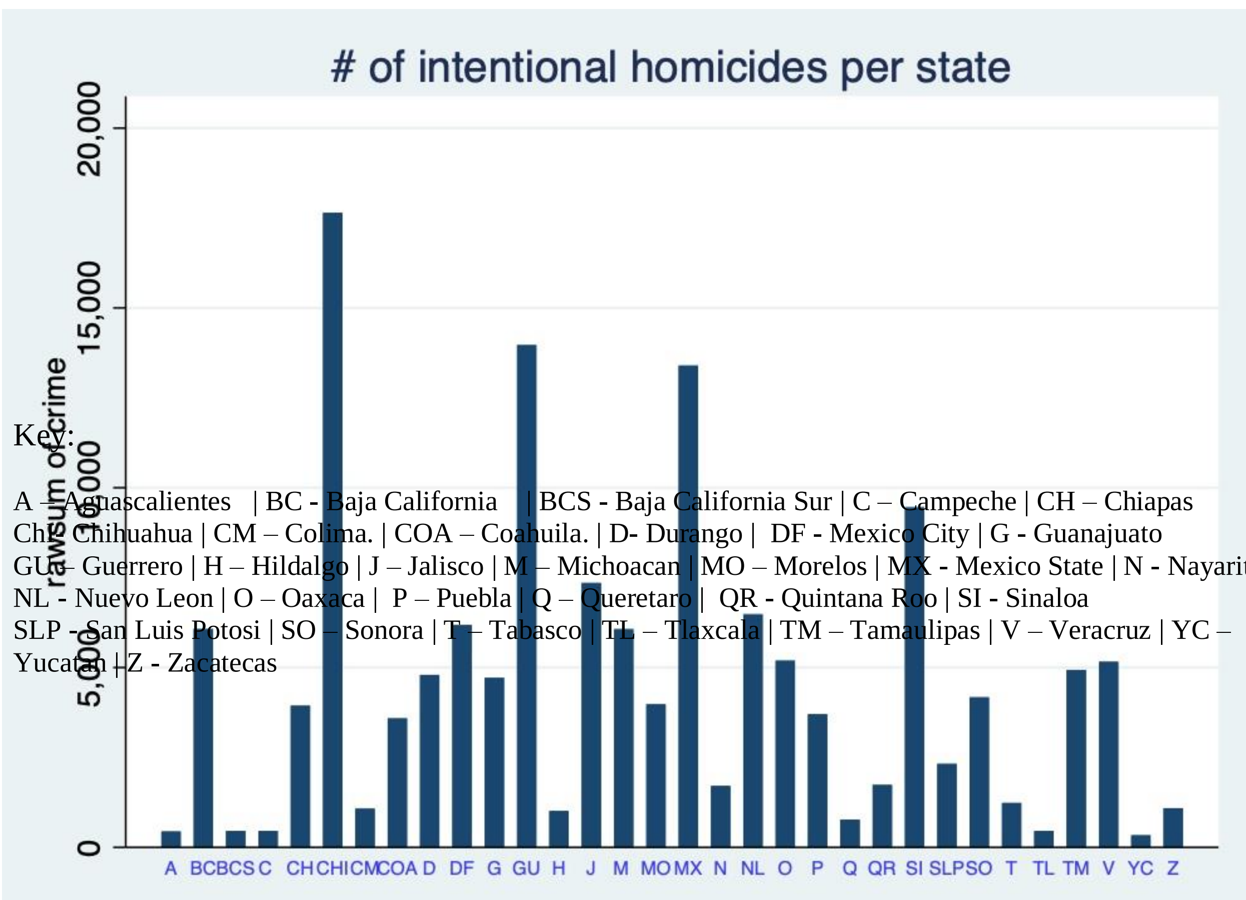
Variation

Variable	Mean	Std.Dev
Intentional Homicides overall	17.237	20.843
between		14.062
within		15.559
Kidnappings overall	1.211	1.388
between		1.010
within		0.974
Extortion overall	5.711	4.934
between		3.771
within		3.212
Vehicle robberies overall	33.717	45.726

between	36.886
within	26.609

Note – Between deviation is measuring the square root of variance across states, i.e., an estimate of variation between states. Within variation is an estimate of variation within states.

Intentional Homicides per State, 2008-2015



Key:

A – Aguascalientes | BC - Baja California | BCS - Baja California Sur | C – Campeche | CH – Chiapas
CHI- Chihuahua | CM – Colima. | COA – Coahuila. | D- Durango | DF - Mexico City | G - Guanajuato
GU – Guerrero | H – Hildalgo | J – Jalisco | M – Michoacan | MO – Morelos | MX - Mexico State | N - Nayarit
NL - Nuevo Leon | O – Oaxaca | P – Puebla | Q – Queretaro | QR - Quintana Roo | SI - Sinaloa
SLP - San Luis Potosi | SO – Sonora | T – Tabasco | TL – Tlaxcala | TM – Tamaulipas | V – Veracruz | YC – Yucatan | Z - Zacatecas

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