The asymmetric impact of out-migration and return-migration on wages in the source country: Evidence from Mexico

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Abstract

This paper studies the effects of the recent increase of returning migrants from the U.S. to Mexico on the wages of workers in Mexico and contrasts the findings with the impact of historical out-migration trends. A stylized model provides the estimated equations and the framework to simulate the effect of out- and return-migration. The empirical estimation shows that returning migrants and non-migrant workers are imperfect substitutes, suggesting that returning migrants acquired human capital abroad that is valued in the home-country labor market. Imperfect substitution generates distributional and sign asymmetries for out-migrant and returnee-induced labor supply shocks of the same magnitude.

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1 Introduction

A million Mexican immigrants left the U.S. between 2009 and 2014.(Gonzalez-Barrera, 2015)[1] The stock of Mexican migrants in the U.S.[2] and migration rates from Mexico to the U.S. have declined, while the number of migrants returning to Mexico has increased.[3] Moreover, as a result of fast changing immigration policy in the U.S., these trends could be permanent and should be understood. The reversal of historical migration patterns is an understudied subject, and its implications are needed to craft any potential policy to cope with the negative side effects in and beyond the Mexican context. The Mexican case is an ideal lab that can provide lessons for low and middle-income countries. More generally, Mexican emigration rates are relatively high for a country of this size (OECD and UN-DESA, 2013), making the economic impacts of migration potentially large, particularly with such a large percent of migrants concentrated in the U.S.[4] This paper contributes by providing results on the effects of recent and historical migration patterns on the wages of Mexican workers, and identifying new asymmetric patterns that are generated by differences between returning migrants and non-migrants.

To estimate key parameters a stylized model provides the empirical framework. Using cross-sectional data from 1960 to 2015, and estimating an equation of relative labor supplies on relative wages, I find that returning migrants and non-migrant workers are imperfect substitutes, and the former earn more. For the preferred estimates, the implied elasticity of substitution[5] between returning migrants and non-migrants ranges from 4.35 to 10.[6] The elasticity of substitution is identified by leveraging variation in pull factors outside the Mexican economy and differential exposure to industry shocks in the U.S. Specifically, the IV relies on the exogeneity of industry growth rates and predetermined weights before the pass of the Immigration Reform and Con-

[1] According to Pew Research Center (Gonzalez-Barrera, 2015)

[2] Pew Research Center estimates (Gonzalez-Barrera and Lopez, 2012)

[3] Calculations based on *Encuesta Nacional de Dinámica Demográfica*

[4] The figure was 85% in 2015 (based on calculations using *Encuesta Intercensal* 2015) and 97.05% in the 2000 census (Caponi, 2010).

[5] The empirical specification provides an estimate of $\partial \ln(w_R/w_{NM})/\partial \ln(L_R/L_{NM}) = 1/\sigma_{RNM}$. σ_{RNM} is the elasticity of substitution.

[6] This parameter can have a minimum value of zero, implying they are perfect complements, and a maximum value of infinity, implying they are perfect substitutes.

trol Act (IRCA) of 1986 and the amnesty that came with it. Industry composition in the U.S. for different education-experience clusters had long-lasting effects on the type of jobs that Mexican workers are likely to obtain in the future. This IV is a strong predictor of the ratio of the labor supply of returning migrants to non-migrants. Moreover, the IV is unable to predict events that pre-date 1980, suggesting that there are not permanent unobservables driving point estimates. Results are also robust to several alternative explanations including out-migrant selection, return-migrant selection, differential assimilation to the Mexican labor market upon returning, relocation to high-wage locations, occupational differences and various other econometric issues.

Imperfect substitution between returning migrants and non-migrants is key in generating an asymmetric impact of out and return migration flows. First-time migrants and non-migrants are perfect substitutes. However, when migrants return, the migration episode creates a new dimension of heterogeneity, and return-migrants become imperfect substitutes to non-migrants. By showing that out-migration and return-migration have asymmetric effects, this paper contributes to the literature studying the impact of migration on labor market outcomes[7] from the source country perspective (Aydemir and Borjas, 2007; Mishra, 2007; Hanson, 2007; Gagnon, 2011; Elsner, 2013a,b). For Mexico, few papers look at the effects of out-migration on wages (Mishra, 2007; Aydemir and Borjas, 2007; Hanson, 2007). I simulate a shock with 7.6 million out-migrants, roughly the size of the Mexican-born population[8] living in the U.S., which allows a closer comparison with existing literature. For the non-migrant population, distributional effects are similar to those found in the literature; it is workers with high-school and some college education who gain the most. But returnees observe smaller effects and different signs for the same shock. Simulating an out and return-migration induced shock of the same size shows that returnee shocks more closely impact the wages of other returnees but have neglectable impacts on non-migrants. The same size out-migration shock generates small losses across the board for the returnee wage distribution but mixed effects for the non-migrant population.

[7] Friedberg and Hunt (1995), Borjas (1999), Card (2005), Card (2001) and Dustmann et al. (2016) provide a summary of the literature looking at the impact of immigration on the host country wages.

[8] Figure based on the Current Population Survey.

This paper builds on the branch of the literature (Cortes, 2008; Card, 2009; Ottaviano and Peri, 2012; Manacorda et al., 2012; LaLonde and Topel, 1991) studying imperfect substitutability between natives and immigrants. The issue of imperfect substitutability appears in contexts in which migrants and non-migrants share a labor market. For instance, in the U.S. and the U.K., this issue is at the center of the debate of whether immigrants negatively affect the wages of natives. Imperfect substitutability is equivalent to immigrants having at most a small negative and possibly a positive impact on natives' wages. This paper broadens this understanding by showing imperfect substitutability from the source country perspective. Imperfect substitution between returning migrants and non-migrants is different from the same concept between natives and immigrants. Intuitively, migrants that return to their country of origin share the same language and culture, and often acquired their formal education in the same institutions as non-migrants.[9] Differences along these and other dimensions become evident when we compare natives and immigrants in the U.S. or U.K.

The imperfect substitution result is consistent with migrants acquiring human capital in the U.S. that is rewarded in the Mexican labor market. First, by exploiting the panel structure of *Encuesta Nacional de Empleo* (ENE) and *Encuesta Nacional de Ocupación y Empleo* (ENOE), this paper shows that out-migrants do not out-earn non-migrants before they leave. In addition, the Mexican Family Life Survey (MxFLS) provides nationally representative evidence supporting the same finding. This evidence stands in marked contrast with wages of returning migrants who consistently earn more. Second, the paper uses the structural model to test whether non-migrants and out-migrants are imperfect substitutes before they leave, and they are not. However, migrants are imperfect substitutes after returning. The test indicates that migrants change after the migration event. Results are consistent with Reinhold and Thom (2013). They use the Mexican Migration Project to find that returns to a year of experience in the United States can be as high as 8 percent in the Mexican labor market. Their paper discards several alternative explanations to the human capital hypothesis, including selection into returning, selection into migration, selection

[9] These are some reasons why Dustmann and Preston (2012) argue immigrants are imperfect substitutes. However, these factors do not exist for returning migrants.

into employment, unobserved skills, etc.[10][11] The combined evidence of existing literature and the new imperfect substitutability result imply that the mechanism that generates imperfect substitution operates while migrants live, work, or study abroad. I add to the existing literature by showing that the specific type of human capital that migrants acquire abroad not only increases their wages, but also makes them imperfect substitutes for non-migrant workers.

Based on the results, it follows that returning migrants compete more directly with each other in the labor market. For Mexico, existing literature has documented that most migrants are geographically concentrated (Hanson, 2007). These stylized facts suggest that shocks that cause return migration concentrate labor market competition regionally, making returning migrants particularly vulnerable, since these shocks are usually accompanied with job losses and other deprivations. The points raised above suggest that policies designed to improve labor market outcomes for returning migrants should be place-based.

In addition to the elasticity of substitution between returnees and non-migrants, this paper estimates the elasticity of substitution across educational attainment and across experience groups. To identify the elasticity of substitution across experience groups, I use the same shock exposure IV. To identify the elasticity across educational attainment groups, I use a similar instrument, but the IV only groups workers by educational attainment. Point estimates imply elasticities of substitution of 4 and 6 across experience and education groups. The main results use newly available census and population count data for the years 2010 and 2015 (including previously available census data).

The set of elasticities of substitution combined with the stylized model facilitate the calcula-

[10]There are theoretical arguments supporting the link between experience abroad and human capital accumulation: Borjas and Bratsberg (1996), Dustmann and Weiss (2007), Dustmann et al. (2011), Dos Santos and Postel-Vinay (2003), Mayr and Peri (2009), and empirical evidence mainly from Europe, including papers by: De Coulon and Piracha (2005), Gang et al. (2000), Barrett and Goggin (2010), Barrett and O'Connell (2001). Additional evidence from Mexico: Zahniser and Greenwood (1998), Li (2018) and Lacuesta (2010). Lacuesta does not find wage-growth with experience in the U.S., but Reinhold and Thom (2013) reproduce his results, showing that data limitations drive Lacuesta's contrarian findings.

[11]Furthermore, existing literature (Kaestner and Malamud, 2014; Fernandez-Huertas, 2011) shows that Mexican migrants to the U.S. are negatively selected from the wage distribution. Evidence from Italy (Bartolucci et al., 2018) and from the U.S. (Lubotsky, 2007) shows that on average returning migrants are also negatively selected from the wage distribution, suggesting that a composition effect is unlikely.

tion of price elasticities. Inspection of the price elasticity formulas shows that a returnee-induced shock has a direct impact on other recent returnees, but only indirect effects on non-migrant workers through similarities in educational attainment and experience. Similarly, outmigrant-induced shocks have a direct effect on non-migrants, but indirect effects on returnees. Moreover, these price elasticities change according to the labor market composition and vary with education, experience and migratory status.

An advantage of using some structure, a nested-CES in this case, is that after estimating a few structural parameters, it is possible to calculate cross effects for 48 skill groups.[12] For the preferred specification, the number of parameters needed to calculate all cross effects exceeds the number of observations in any data set currently available, and it is not possible to get these effects without any structure. A disadvantage of the model is that it imposes separability, i.e., substitution within a subgroup is not affected by inputs in other subgroups. It also assumes that the ease of substitution between factors not in the same group is constant. Lastly it assumes that workers that share all characteristics in common are perfect substitutes. According to Hamermesh (1996) this is the most problematic assumption. To address this limitation, this paper carefully tests for grouping structures by grouping workers into different educational attainment categories and also testing for imperfect substitution. In this sense, the concerns regarding that last assumption are minimized.

An additional advantage is that the structure facilitates the counterfactual analysis of only allowing first-time migrants in out-flows. In practice, out-flows combine first-time migrants and repeat migrants. But repeat migrants are already imperfect substitutes to non-migrants. Thus, from observational data it would not be easy to disentangle the heterogeneity and the asymmetry of the impact of different flows discussed in this paper.

The structure of the paper is as follows. Section 2 describes the data, variables, and the theoretical framework. Section 3 discusses identification. Section 4 presents and discusses point estimates. Section 5 presents simulation results. Finally, section 6 concludes.

[12] 6 educational attainment groups subdivided into 8 experience groups.

2 Data and Methods

2.1 Methods

I use a stylized theoretical model of labor demand that groups worker types by education, experience and returnee status, following the work of Ottaviano and Peri (2012), Manacorda et al. (2012), Aydemir and Borjas (2007), Borjas (2003), Card and Lemieux (2001), and Welch (1979).

To derive the model, assume that the market is competitive; hence, factors are paid according to their marginal product. In addition, assume that national production follows a Constant Elasticity of Substitution production function:[13]

$$Q_t = \tilde{A}_t \left(\theta_{Kt} K_t^{\nu} + \theta_{Lt} L_t^{\nu}\right)^{1/\nu} \tag{1}$$

At time t, Q_t is aggregate output and has a price of 1, K_t is physical capital, L_t is a CES aggregate of different types of labor, $\tilde{A}_t$ is total factor productivity. $\nu = 1 - 1/\sigma_{KL}$ and σ_{KL} is the elasticity of substitution between capital and labor ($-\infty < \nu \leq 1$). θ_{Kt} and θ_{Lt} are time variant technology parameters that shift the production frontier, with $\theta_{Kt} + \theta_{Lt} = 1$.

2.2 Worker Heterogeneity

The main specification follows the nest structure in figure 1. From right to left, workers in each branch of the diagram share more characteristics in common. For example, workers in the branch labeled "High School" have high school education. Moving to the left, workers with high school education can fall in the 1 to 5 years of experience or any other cell up to 36 to 40 years of experience. The last nest to the left has workers with high school education, with 1 to 5 years of experience, who are either non-migrant or returnee workers. This pattern is reproduced for every educational attainment cell.

[13]This functional form is flexible and includes several special cases. In contrast to the U.S. case, for Mexico there is no strong evidence favoring a unique functional form such as a Cobb-Douglas.

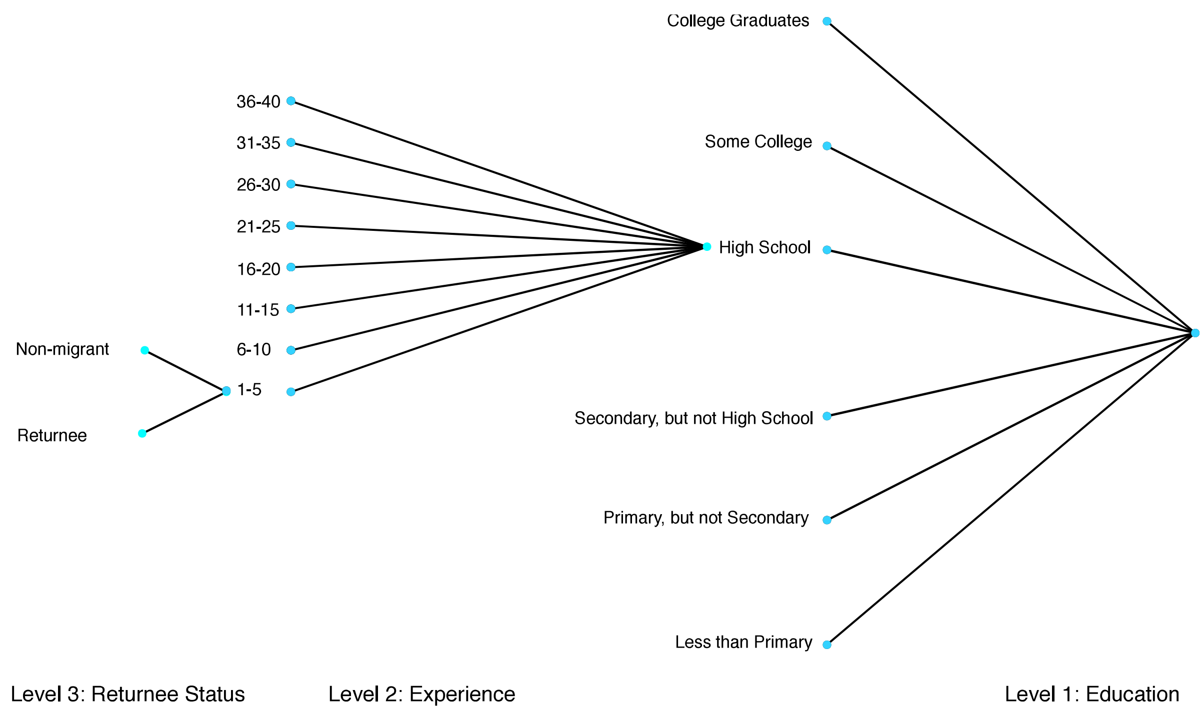


FIG. 1. –Nest Structure

$$L_t = \left[\sum_e \theta_{et} \left[L_{et} \right]^{1-1/\sigma_e} \right]^{1/(1-1/\sigma_e)} \tag{2}$$

L_t is total aggregate labor. θ_{et} is a technology parameter that shifts the production frontier and can be given the interpretation of skilled bias technical change. σ_e is the elasticity of substitution across educational attainment groups. L_{et} is a labor-factor composite with education e, e.g., college educated workers.

$$L_{et} = \left[\sum_x \theta_{ext} \left[L_{ext} \right]^{1-1/\sigma_x} \right]^{1/(1-1/\sigma_x)} \tag{3}$$

L_{ext} is an armington aggregate of labor factors with education e, but different experience x. σ_x is the elasticity of substitution across experience groups. Furthermore,

$$L_{ext} = \left[\sum_k \theta^k_{ext} \left[L^k_{ext} \right]^{1-1/\sigma_m} \right]^{1/(1-1/\sigma_m)} \quad k = m, nm. \tag{4}$$

L^n_{ext} is a labor-factor with education e, experience x, and $n = m, nm$. n indexes returnees m or non-migrants nm. σ_m is the elasticity of substitution between returnees and non-migrant workers.

2.2.1 Testing for imperfect substitution between returnees and non-migrants

Equation 4 has as special cases a Leontief, a Cobb-Douglas, and a Linear function. If the elasticity of substitution between returnees and non-migrants is $\sigma_m = \infty$, the CES aggregate in 4 converges to a linear functional form, and it implies that returnees and non-migrants are perfect substitutes. In contrast, if $\sigma_m < \infty$, they are not perfect substitutes. Lastly, σ_m should be positive, for the model to be a well-defined production function. A negative sign is a misspecification test, suggesting that the model does not fit the data.

2.2.2 Deriving the estimating equations

For the last nest in 4, profit maximization gives $\frac{\partial Q_t}{\partial L_{exmt}} = w_{exmt}$, i.e., the marginal product of labor equals wages. Taking logs on both sides and differencing two types of labor in the same nest, e.g., differencing returnees and workers who did not migrate, produces equation 5. Rearranging gives the following estimating equation:

$$\ln w^m_{ext}/w^{nm}_{ext} = -\frac{1}{\sigma_m} \ln L^m_{ext}/L^{nm}_{ext} + \ln \theta^m_{ext}/\theta^{nm}_{ext} + \tilde{\varepsilon}^{mnm}_{ext} \tag{5}$$

Equation 5 states that relative wages depend on the log ratio of technology shifting parameters $\ln \theta^m_{ext}/\theta^{nm}_{ext}$, minus the ratio of relative labor supplies, $\ln L^m_{ext}/L^{nm}_{ext}$. The negative sign in front of the relative supplies is expected, but not imposed; instead, the data will reveal the sign.

From equation 5 σ_m, θ^m_{ext}, and θ^{nm}_{ext} are estimated. With these parameters, L_{ext} in equation 4 is calculated. The process is repeated for every nest.

$$\ln w_{ext} = \gamma_t + \xi_{et} + \ln \theta_{ext} - 1/\sigma_x \ln L_{ext} \tag{6}$$

Profit maximization with respect to labor-factor L_{ext} and some algebra yield equation 6,[14] needed to estimate σ_x.

$$\ln w_{et} = \delta_t + \ln\theta_{et} - 1/\sigma_e \ln L_{et} \tag{7}$$

A similar process generates equation 7,[15] needed to estimate σ_e, the elasticity of substitution across education groups.

The key parameters are the elasticities of substitution between labor-factors. By combining these elasticities with factor demand theory, it is possible to simulate the cross effect of migration on wages.

2.3 Data

Data on wages, labor force participation, educational attainment, occupational classification, and demographic characteristics, such as age and gender, come from the Integrated Public Use Micro-data Series (IPUMS) International for Mexico (Mexican Census) for the years 1960, 1970, 1990, 2000, and 2010. I combine these data with the five-year inter-census count for the years 1995 and 2015 from *Instituto Nacional de Estadísticas y Geografía* (INEGI).

Encuesta Nacional de Ocupación y Empleo (ENOE) and *Encuesta Nacional de Empleo* (ENE) provide yearly labor market outcomes data from 1995 to 2016. ENOE is an ongoing labor force survey that has a panel structure. It follows individuals in Mexico for five quarters, recording their labor force participation, income, educational attainment, and hours usually worked among other variables. A strength of ENOE compared to the Mexican census and population counts is that hours worked and hourly wages are observed. It is also possible to observe out-migrants before they move abroad. But a limitation is that it only captures the flow of returnees and not the stock, which is the relevant metric for this paper.

For the instrument, industry shares and growth come from the U.S. census, the American

[14] Where $\gamma_t = \ln\left(\tilde{A}Q_t\right)^{1-\nu} + \ln\theta_{Lt} + (1/\sigma_e - 1/\sigma_{kl})\ln L_t$ and $\xi_{et} = \ln\theta_{et} + (1/\sigma_x - 1/\sigma_e)\ln L_{et}$.

[15] Where $\delta_t = \ln\left(\tilde{A}Q_t\right)^{1-\nu} + \ln\theta_{Lt} + (1/\sigma_e - 1/\sigma_{kl})\ln L_t$

Community Survey, and the Current population Survey.This paper uses the U.S. census for the years 1960, 1970, 1990, and 2000, as well as American Community Survey (ACS) for the years 2001 to 2016. I pool the ACS for the years 2009, 2010 and 2011 to generate statistics for the years 2010, and the years 2014, 2015 and 2016 for the year 2015.

Finally, the Mexican Family Life Survey (MxFLS) facilitates the evaluation of the impact on wages by providing a count of the number of returnees, a key input for the simulations. The MxFLS has a panel structure at the individual level that covers three waves between 2002 and 2009. It has information on migrants' wages before they left and migration history. An advantage of MxFLS is that it identifies migrants that returned to Mexico 5 or more years ago. There has been some attrition, but the survey provides weights that adjust the national population to the base year in 2002, and to 2009.

2.4 Definition of Variables

For the estimation of the elasticity of substitution between returnees and non-migrant workers, the Mexican census starting in the year 1990 asks if a worker lived abroad in the past 5 years, and this is used to identify returnees. Returnee counts include migrants with and without documents. Since the data come from a national census, everyone is counted. However, the census does not distinguish undocumented migrants. These data do not identify workers who returned to Mexico more than 5 years ago.

To calculate the supply, salary and wages, I restrict the samples to workers aged 18 to 64 who are not enrolled in school. Workers are grouped according to education and potential experience, which is calculated using age - experience - 6. In accordance with existing literature, I assume that workers with less than 12 years of education began working at the age of 17, those with 12 years of education at the age of 19, workers with some college education at the age of 21, and workers with a college degree at 23, while workers with postgraduate education started working at the age of 25. Workers with less than 1 year or more than 40 years of experience are dropped from the sample. Only workers who are either employed or unemployed are included.

Wages are average log monthly earnings for each skill-cell and do not include the self-employed. Only workers who report positive earnings and are not enrolled in school form part of the sample. Top coded incomes are multiplied by 1.5. Finally, average log earnings refer to the mean of log monthly earnings. To obtain hourly wages, ENE and ENOE data are used. A deflator that has March of 2015 as its base is used to deflate wages. Data to construct the deflator was obtained from *Instituto Nacional de Estadísticas y Geografía* (INEGI).

The sample restrictions for wages and labor supply differ because they must meet different criteria. Wage samples reflect a stable composition of the prices paid to given skill levels. In contrast, the goal of the labor supply sample is to measure an aggregate quantity. These differences in sample restrictions follow a long tradition in this branch of the literature, e.g., Katz and Murphy (1992); Borjas (2003); Ottaviano and Peri (2012); Aydemir and Borjas (2007); Manacorda et al. (2012); Card and Lemieux (2001)

3 Identification

The proposed IV leverages variation in differential exposure to "shocks" to the U.S. economy. In 2007, 12.8 million Mexicans were living in the U.S.,[16] and this figure has been at least a million since the 1980s. Given the large recent figures, and the links between Mexican immigrants and Mexico, undoubtedly, shocks to the U.S. economy impact the labor supply in Mexico. For example, positive shocks to the U.S. economy reduce the likelihood that Mexicans return to Mexico. These shocks also affect the labor supply in Mexico via migration and remittances (changing the likelihood of joining the labor force). The million migrants that returned from the U.S. to Mexico between 2009 and 2014[17], in the recessionary environment, is evidence of the relevance of the proposed mechanism.

The IV uses predetermined employment shares at the industry level in 1980 in the U.S., for workers with education e and experience x. These weights do not consider any migrant clusters.

[16] 12.8 million was the peak of the stock

[17] See Gonzalez-Barrera (2015) for exact figures.

Moreover, weights precede the passage of IRCA 1986 and the amnesty the came with it. Arguably, the economic conditions around IRCA 1986 had long lasting effects on the type of jobs that specific Mexican-born demographic groups are likely to get in the future.[18]

Formally,

$$\hat{L}_{ext}^{U.S.} = \sum_{i} \omega_{iext_0}^{U.S.} \left(1 + \Delta \ln L_{it}^{U.S.} / \ln L_{it}^{U.S.}\right) \tag{8}$$

$\hat{L}_{ext}^{U.S.}$ predicts shocks to workers with education e and experience x in period t in the U.S., and it's an IV for $\ln L_{ext}^{m}/L_{ext}^{nm}$ in equation 5. $\omega_{iext_0}^{U.S.}$ are U.S. industry shares in 1980 that weight the U.S. labor supply $L_{it}^{U.S}$ in industry i.[19]

The IV satisfies the exclusion restriction on two fronts. First, the estimating equation is one of labor demand in Mexico for specific education-experience labor markets, but the IV is a labor supply supply shifter. Second, the IV exploits variation outside the Mexican economy. Formally:

$$E\left[\tilde{\varepsilon}_{ext}^{mnm} | \hat{L}_{ext}^{U.S.}, \theta_{ext}^{m}/\theta_{ext}^{nm}\right] = 0 \tag{9}$$

The identifying assumption is that there are not time-varying unobserved shocks that simultaneously affect relative wages for returnees and non-migrants (within education-experience clusters) in Mexico, and also correlate with industry composition in the U.S. in 1980. Moreover, unobserved shock should not simultaneously affect industry growth in the U.S. and relative wages in Mexico.

Notice that shocks to the U.S. that affect the entire Mexican economy are differenced out in the key specification (equation 5), and the same happens to fixed unobservables. From specification 5, it follows that any variation in efficiency in an education-experience cell is canceled out. Skill-biased technological change falls in this category. Moreover, the inclusion of $\theta_{ext}^{m}/\theta_{ext}^{nm}$ in equation

[18] The IV reflects characteristics of the Bartik instrument (Bartik, 1991), but differs so that it can be used for markets of workers with the same experience and education.

[19] Existing literature has estimated $1/\sigma_m$ either without instrumenting for the relative labor supplies (Ottaviano and Peri, 2012) in equation 5 or by directly using the ratio of the total populations in working age (Manacorda et al., 2012), as a robustness check.

5 controls for relative productivity between returnees and non-migrants. The latter includes controls for time varying and non-varying terms that affect relative supplies and wages.

Lastly, equations 6 and 7 require the use of instruments. Specifically, the estimates of $1/\sigma_x$ and $1/\sigma_e$ can be biased because the labor supply for education groups, experience groups, or migrants over a long period of time can be endogenous. The stylized model sketched above provides some guidance. Since these are demand equations, variables affecting supply, but not demand, can be instruments.

In contrast to existing literature,[20] this paper uses the IV in equation 8 as a supply shifter to identify the labor demand slope and thus σ_e and σ_x in Mexico. To estimate σ_e, weights are added over educational attainment groups only, i.e, $\omega_{iet_0}^{U.S.}$.

To estimate the above equations, I assume that $\theta_{ext}^{m}/\theta_{ext}^{nm}$, θ_{ext}, and θ_{et} can be decomposed into additively separable terms (Ottaviano and Peri, 2012; Manacorda et al., 2012).[21] In practice, these terms can be captured by fixed effects (for the types of labor), time-fixed effects, and an idiosyncratic error term. In addition, for a given nest, $\sum_{i(n+1)\in i(n)} \theta_{i(n+1)t} = 1$.

3.1 Validating the Research Design

The identifying assumption requires for unobserved shocks to not affect wages or relatives wages through other channels, except for the effect on relative labor supplies. A way to check for the plausibility of this assumption is to test for pre-existing trends. For instance, if the IV can predict changes in wages before the period of study, it would cast doubts on the research design. The latter would imply that there are permanent unobservables driving the results. If the effects are only present from 1990 onward, this gives reassurance that differential exposure to industry shocks in the U.S. are likely generating the desired exogenous variation.

A limitation is that the question that identifies returnees is only available from 1990 onward.

[20]Existing literature (Borjas, 2003; Aydemir and Borjas, 2007; Ottaviano and Peri, 2012) has leveraged variation in immigrant's labor supply or emigrant (immigrant) outflows (inflows) to identify $1/\sigma_x$ and $1/\sigma_e$.

[21]The same assumption is needed to identify other technology parameters in the model. Other papers that do not test for imperfect substitution assume separability (e.g. Aydemir and Borjas, 2007, Borjas, 2003, and Card and Lemieux, 2001).

Therefore, I implement the test on the levels of log wages, instead of the ratio. If the instrument impacts the levels of wages, undoubtly, it will also impact the ratios.

To check for pre-existing trends, I look at industry shares in the U.S. in 1980 with the highest Rottemberg weights. The IV is most sensitive to these industries, and they also give you an intuitive idea of where the variation is coming from (Goldsmith-Pinkham et al., 2018). Table 1, columns 1 through 5, check that there are no effects of key industries in the U.S. on the dependent variable. All variables are residualized. Schools, construction, Landscape and Horticultural Services and Services to Dwelling and Buildings are all insignificant. The latter suggests that there are no permanent unobserved shocks affecting wages in Mexico and industries in the U.S. Eating and drinking places are the exception. Despite the significance, the sign is in the wrong direction. Differential exposure to a thriving industry in the U.S. should drive wages upwards in Mexico, not downwards.

To further explore this anomaly, column 6 of Table 1 shows the result of regressing all 1980 industry shares on log wages in Mexico in 1960 and 1970. Combining all the variation suggests that the effect before 1980 is null, reducing the concerns on the statistical significance of Eating and Drinking Places.

Additional support to the no pre-trends view comes from column 7, where the explanatory variables is the IV in equation 8. The IV cannot predict wages in 1960 and 1970. The coefficient is 1.29 but not significant. Similarly, column 8 has as dependent variable the natural logarithm of the labor supply in 1960 and 1970 and regresses it on the IV. The IV cannot predict the labor supply before 1980. Overall, the empirical evidence supports the identifying assumption, equation 9.

Table 1
Validating the research design

	(1) Construction	(2) Eating Places	(3) Schools	(4) Landscape and Horticultural Services	(5) Services to Dwelling and Buildings	(6) All Industry Shares	(7) IV	(8) Labor Supply
Industry Share	-0.05	-1.10***	0.30	-5.88	1.54	-0.00		
	(0.27)	(0.39)	(0.44)	(4.47)	(4.03)	(0.00)		
IV							21.84	-67.29
							(47.49)	(202.15)
R^2	0.00	0.23	0.00	0.06	0.00	0.00	0.03	0.01
N	96	96	96	96	96	23424	96	96

NOTE. – The table presents regressions of the residualized mean of log wages for the years 1960 and 1970 on key industry shares. Columns 8 and 9 use the IV as dependent variable, but column 9 uses the log of the labor supply in 1960 and 1970 as the dependent variable. Columns 7 presents cluster robust standard errors. All other columns display bootstrap standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.2 Establishing the Existence of the First-Stage

Table 2 displays the coefficient of the IV on relative labor supplies. Notice that the IV is a strong predictor of relative supplies for the pooled data including the years 1990, 2000, 2010 and 2015, in contrast to what we observed for the pre-analysis period in 1960 and 1970. The IV implies that positive economic shocks reduce the ratio of returning migrants to non-migrants, i.e.,when the U.S. economy is doing well, fewer migrants return to Mexico and more Mexicans leave the labor force to move to the U.S.

Table 2
First-Stage regressions

	(1)	(2)	(3)	(4)
All	-35.2***	-86.6***	-66.3***	-81.5***
	(9.49)	(18.20)	(8.11)	(20.38)
Females	-26.3***	-94.6***	-64.1***	-65.1***
	(7.06)	(11.40)	(8.22)	(10.14)
Males	-37.1***	-84.1***	-68.8***	-90.2***
	(10.14)	(19.71)	(9.12)	(24.57)
Year FE	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES

NOTE. – The table displays the reduced from regression of the IV on the ratio of labor supplies. All Population, Females and Males refer to the samples. Cluster robust standard errors in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The first column of Table 2 shows the effect is present when no fixed effects are included in the model. Overall, the sign and significance is consistent across specifications in columns 1 through 4. Moreover, looking across groups, the significance and magnitude is also consistent within models. Compared to column 1, the coefficients grow as more fixed-effects are included, but it's not possible to point to a particular factor that could be driving this effect. What we know is that 1) from the previous section, no unobserved factors seem to be driving the variation, and 2) since the education-by-experience fixed effects is demeaning the labor supplies, and other non-parametric controls are present, it is inevitable to have some variation.

The overall picture shows that the IV predicts changes in the ratio of labor supplies, and this effect is robust to increasing levels of non-parametric controls that leave very little variation left. For instance, the fixed-effects in column 4 absorb 99.2% of the IV variation. Additional fixed-effects are equivalent to closing channels through which the IV can have an effect on relative supplies, and they make it more likely that the exclusion restriction in equation 9 holds. I'll show in the next sections, that despite the variation in the first-stage, the coefficient of the second stage is fairly stable.

3.3 Local Average Effect Interpretation of the IV

As long as within each education-experience cell there are individuals that respond to U.S. economic shocks by entering or leaving the labor force, the IV will be relevant. These are compliers in the language of Imbens and Angrist (1994). Focusing on our unit of observation, I find it highly implausible to have never-takers. This possibility implies that no-one within each education-experience labor supply cell leaves or enters the labor force in Mexico in response to shocks to the U.S. economy.

Table A1 in the appendix displays evidence supporting a heterogeneous response interpretation of the IV. Column 1 includes the full sample for comparison. Notice that excluding workers who graduated college in column 4 or excluding workers with at least high school education (column 3), keeps points estimate fairly stable. In contrast, column 5 excludes the lower and upper tails of the educational attainment distribution, and the magnitude of the coefficient goes up by approximately 25%.

Intuitively, results in Table A1 make sense. Returns to education are higher in Mexico than in the U.S., which implies that workers with a college degree are less likely to leave the labor force in Mexico in response to economic shocks in the U.S. Workers with less than primary education should be less responsive, too. They earn less and should find find it harder to finance migration to the U.S. Lastly, existing evidence (Kaestner and Malamud, 2014) suggests that migrants are drawn from the middle of the educational attainment distribution.

In sum, the IV is capturing a weighted effect of heterogeneous responses across education-experience cells. More weight is given to cells in the middle of the educational attainment distribution.

4 Results

Table 3 presents summary statistics of relative wages and supplies. The third column shows, for each educational attainment group, the proportion of workers who were living abroad five years ago. The fourth column presents relative wages, defined as the wages of returnees divided by the wages of non-migrants. Returnees consistently earn more than non-migrants. A central hypothesis in this paper is that due to imperfect substitutability, returnees and non-migrants compete more directly with each other in the labor market. Table 1 presents a pattern consistent with this paper's central hypothesis: relative wages decrease as the number of returnees increases.

The top 25 occupations for non-migrant and returnee workers, according to employment shares, can be seen in Table A2. Occupations follow the Mexican National Occupation Classification System. The column labeled "rank" shows the importance of a specific type of occupation. Notice that the relative importance of occupations differs only slightly across returnee status.[22]

4.1 Inverse of the elasticity of substitution between returnees and non-migrant workers: $1/\sigma_m$

Prima facie evidence of imperfect substitution comes from panel (a) of Figure 2. The y-axis is the log ratio of returnees to non-migrant wages, and the x-axis is the log ratio of their labor supplies. The negative slope suggests that if relative supplies change by one unit, there would be a less than perfect pass-through to relative wages. For perfect substitutes, an increase in relative supplies would decrease the wages of returnees and non-migrants by the same amount, leaving the relative ratio of wages intact. As a consequence, the line should be perfectly flat. But using raw data and none of the controls suggested by the theoretical model shows that returnees and non-migrants are imperfect substitutes.

The estimating equation used in Table 4 is 5. This specification eliminates any common trends affecting workers with the same education and experience even if these trends are time variant. The fixed effects included in the model control for differences in their relative productivity, $\theta^{m}_{ext}/\theta^{nm}_{ext}$. Standard errors are clustered over education-experience cells.[23] For comparison, panel

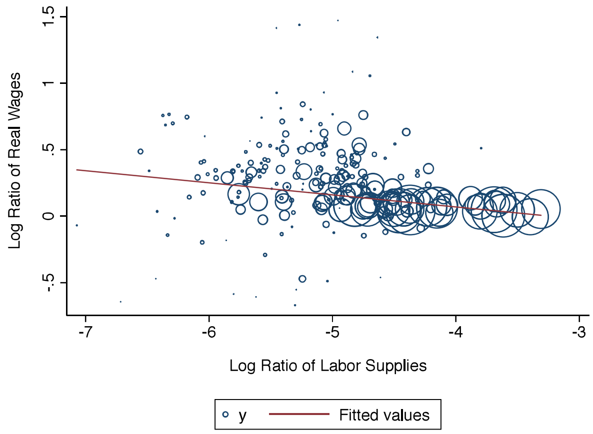
[22]When returnees and non-migrants work in the same industries, they specialize in slightly different things. For example, many returning migrants in the agricultural sector work in non-traditional export-oriented industries, such flowers and fruits.

[23]This clustering imposes the restriction that observations of workers with the same education and different experience are uncorrelated (Cameron and Miller, 2015). For example, observations of high school graduates with 30

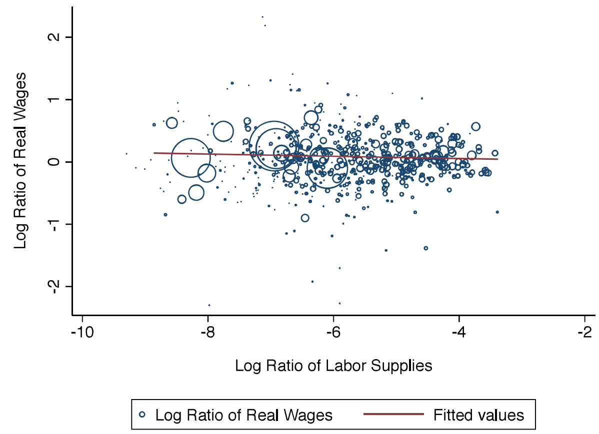
Table 3
Relative wages and labor supply

	Education	Relative Supply (%)	Relative Wages (%)
Year 1990:			
	Less than primary	0.27	150.29
	Primary education but not secondary	0.27	135.25
	Secondary education but not high school	0.24	138.04
	High school graduate	0.45	182.30
	Some college	0.45	208.37
	College graduate	0.60	190.63
Year 1995:			
	Less than primary	0.49	151.27
	Primary education but not secondary	0.76	116.50
	Secondary education but not high school	0.66	129.48
	High school graduate	0.87	156.95
	Some college	0.83	131.31
	College graduate	0.72	141.14
Year 2000:			
	Less than primary	0.44	136.70
	Primary education but not secondary	0.58	124.51
	Secondary education but not high school	0.55	126.77
	High school graduate	0.61	141.74
	Some college	0.69	136.70
	College graduate	0.69	176.08
Year 2010:			
	Less than primary	1.63	112.30
	Primary education but not secondary	2.20	106.08
	Secondary education but not high school	1.79	105.12
	High school graduate	1.49	115.06
	Some college	1.08	109.97
	College graduate	0.97	147.62
Year 2015:			
	Less than primary	0.83	112.49
	Primary education but not secondary	0.98	107.52
	Secondary education but not high school	0.82	107.29
	High school graduate	0.79	118.32
	Some college	0.65	138.09
	College graduate	0.69	164.96

NOTE. –Table 1 uses the Mexican census and population counts for 1995 and 2015. Relative supply is the ratio of the labor supply of returnee to non-migrant workers. Relative wage is the ratio of their wages.



(a) Imperfect substitution post-migration



(b) No imperfect substitution pre-migration

FIG. 2. –The left panel illustrates the elasticity of substitution between returnees and non-migrants using data from the Mexican Census. The right panel illustrates the elasticity of substitution between non-migrants and migrants before they leave. The samples include males and females. Circles are proportional to the sample size used to obtain the average wage in each education-experience-year cell. Migrants' wages are recorded pre-migration.

A, in columns 1, 2, 3 and 4 displays weighted least squares estimates, while columns 5 to 9 display IV results.

IV estimates in columns 4 through 8 of panel A in Table 4 are negative, and suggest that returning migrants and non-migrants are imperfect substitutes. In particular, the models imply an elasticity of substitution that range from 3.7 to 16.7. Point estimates vary, but are not statistically different from each other.

Moving to the female-only sample in panel B of Table 4, implicit inverse elasticities of substitution range from 3.4 to 25 for the IV estimates. In other words, females in the labor force that returned to Mexico and non-migrants in Mexico are imperfect substitutes. Results are less precise for this sample and have wide confidence intervals that cover previous point estimates.

The male-only sample in panel C of Table 4 implies elasticities of substitution for the IV estimates that range from 3.3 to 8.3. Results are precise and in line with the other samples.

Focusing on IV estimates suggests a trade-off between saturating the model with fixed-effects and leaving relevant variation for identification. For example, in panel C of Table 4, moving from column 7 to column 8 reduces the strength of the F-statistic of the excluded instruments by more

and 35 years of experience would be considered as uncorrelated. Clustering over education does not change results.

than 75%.[24] In column 8 only 0.8% percent of the variation in the IV remains. The lack of statistical significance in column 8 of panel A and B is also related to the trade-off.[25]

Existing estimates for the U.S. produced elasticities (in absolute value) of approximately 20 (Card, 2009; Ottaviano and Peri, 2012), and a lower bound of 4 (Cortes, 2008). In the U.K., the parameter is considerable smaller, at 7.8, due to the fact that it is other immigrant wages that absorb most of the impact of the increased labor supply (Manacorda et al., 2012). Intuitively, the elasticity in this paper should be larger: returnees speak fluent Spanish, acquired education in the same country,[26] and may have valuable work experience in the Mexican labor market. [27] [28]

Overall, results consistently imply that returning migrants and non-migrants are imperfect substitutes. Moreover, IV estimates moved in the expected direction: unobserved shocks correlate positively with relative supplies and wages, driving point estimates upward. The IV corrects for the latter, and measurement error that potentially drives points estimates to zero.

[24]I implement a weak instruments test that is robust to heteroskedasticity, autocorrelation and clustering (Olea and Pflueger (2013); Pflueger and Wang (2015)) and the F-statistic exceeds the critical values.

[25]Direct estimation of the IV on the ratio of wages demonstrates the consequences of only having 0.8% of the variation left.

[26]Although there are returnees who may have moved early in their life and may have acquired their education in the U.S., they constitute a small fraction of the total.

[27]Imperfect substitutability in the Mexican labor market can be driven by on-the-job training in the U.S. In contrast, at the destination, this result could be explained by the lack of relevant experience that commensurates with migrant's educational attainment. For instance, it has been documented in the U.S., U.K., and Germany (Borjas and Katz, 2007; Dustmann et al., 2013, 2016) that immigrants downgrade and do jobs that require less formal education.

[28]Studying these impacts from the source country perspective reduces concerns that it might be inappropriate to bin together foreign and native workers with potentially different experience and education (Dustmann et al., 2016) or that sampling errors attenuate effects (Aydemir and Borjas, 2011). The latter makes the case for measuring shares of migrants. The concern is somewhat reduced for measuring levels.

Table 4
Inverse of the elasticity of substitution between returning migrants and non-migrants

Panel A: Full Sample

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.09***	-0.06***	-0.05*	-0.08***	-0.27***	-0.06***	-0.13**	-0.10
	(0.01)	(0.01)	(0.03)	(0.03)	(0.05)	(0.02)	(0.06)	(0.08)
N	223	223	223	223	191	191	191	191
F-statistic					90.0	19.4	47.9	10.2
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

Panel B: Females

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.13***	-0.08***	-0.04	-0.06	-0.29***	-0.12***	-0.14	0.15
	(0.02)	(0.03)	(0.06)	(0.09)	(0.08)	(0.04)	(0.10)	(0.24)
N	197	197	197	197	183	183	183	183
F-statistic					50.0	58.5	42.9	25.7
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

Panel C: Males

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.10***	-0.07***	-0.05	-0.11***	-0.30***	-0.12***	-0.13**	-0.23***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.06)	(0.02)	(0.06)	(0.07)
N	217	217	217	217	190	190	190	190
F-statistic					95.0	15.6	40.6	8.58
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

NOTE. –Wage calculations include full time workers, who are not self-employed, and not enrolled in school. Labor supply includes the total count of workers (males and females), and the self-employed. The model is weighted by the inverse of the variance of the dependent variable. Robust standard errors are reported in parenthesis, clustered over education-experience cells. F-statistic refers to the effective F-statistic of excluded instruments Olea and Pflueger (2013). Table includes the years 1990, 1995, 2000, 2010, and 2015 but the IV results exclude the year 1995 due to data availability. * p <0.1, ** p<0.05, *** p<0.01.

4.2 Robustness of the elasticity of substitution between returnees and non-migrants

Identifying the correct parameter

For the U.S. and U.K Dustmann and Preston (2012) argue that immigrants downgrade within education-age cells and have different assimilation curves. With a simple model they show that the initial downgrading and the difference in assimilation rate might cause point estimates to indicate imperfect substitution between migrants and natives, when there is not.

The Mexican case is very different. First, I do not study migrants and natives, but instead, a more subtle different between returning migrants and non-migrants. Second, assimilation to the local culture and language is simply not present. Ultimately, the question of whether they have differential wage gains that are related to experience or other observables is an empirical question.

To explore this concern, I use the first round of the Mexican Family Life Survey (MxFLS) in 2002. This sample is nationally representative. In particular, MxFLS provides data on wages and the full history of migration episodes to the U.S. for every individual in the sample. Table A4 in the appendix tests the hypothesis on assimilation trends. Column1 shows that controlling non-parametrically for education and experience, return migrants earn a premium of at least 5%.

The relevant hypotheses in Table A4 are whether return-migrants earn more as they gain experience or education, relative to non-migrants. Columns 2 through 4 reject the null hypothesis that returning migrants progress faster as they gain more experience. Columns 4 through 6 reject the hypothesis that returning migrants progress more with more education, relative to non-migrants.

Empirical results support the view that return-migrants earn more, and that this is a level difference not related to differential progress.

Similarity of occupations across returnee status

A potential concern is that returning migrants are "upgrading" or having a distribution of occupations that is not congruent with their educational attainment. If the distribution of occupations of returning migrants and non-migrants is very different, one might argue that the approach I propose in this paper is only capturing this difference. To check for this possibility, I calculate the Duncan Dissimilarity Index. This index provides a number that tells us how many returnees would have to re-locate across occupations to exactly match the distribution of non-migrants.

$$\text{Duncan Dissimilarity Index} = \frac{1}{2}\sum_{i}\left|\frac{r_i}{R} - \frac{nm_i}{NM}\right| \tag{10}$$

The index is calculated by adding half the absolute value of the difference in the proportion of workers in every occupation. The fraction of returnees in occupation i is r_i/R, and for non-migrants it is $\frac{nm_i}{NM}$.

I use the Mexican census and MxFLS data to calculate the Duncan Index. In particular, the MxFLS offers an advantage by identifying anyone who ever migrated. Thus, the MxFLS is able to capture "long-term upgrading". But the limitation is that I am using census data to actually estimate the elasticity of substitution between returnees and non-migrants. In this sense, the MxFLS is only suggestive. Table A5 displays the index for different educational attainment groups.[29] Table A5 shows that the index is 2.45% on average. Similarly, I use the Mexican census and population counts for the years 2010 and 2015.[30] The most dissimilar group in Table 5 is the one with less than primary education, with a a value of 2.03%. For this sample, the average of the dissimilarity index is 1.36%.

In sum, the distribution of occupations between returnees and non-migrants is roughly the same. Using different sources of data, I find that only between 1.36% to 2.45% of returnees would have to be shuffled across occupations to match the distribution of non-migrants.

[29] Educational attainment groups are reported according to the data source.

[30] In particular, the classification in these years is the same, whereas for 2000 and 1990 is different.

Table 5
Dissimilarity of occupations across educational attainment groups

Educational Attainment Group	Dissimilarity Within Educational Attainment Group
Less than primary	2.03%
Primary education but not secondary	1.14%
Secondary education but not high school	1.65%
High school graduate	1.27%
Some college	.66%
College graduate	1.44%
Mean	1.36%

NOTE. – This table displays the Duncan Dissimilarity Index of occupations between returnees and non-migrants using census and population count data for the years 2010 and 2015. The sample is restricted to these two round to assure consistency in occupation classification.

Attenuation bias

Aydemir and Borjas (2011) argue that proportions are measured with sampling error, which has the undesired effect of biasing point estimates. The authors show that in certain applications, the bias can be so severe as to reverse the true sign of the parameter of interest. For the empirical results in Table 4, the equivalent of the proportion is the key explanatory variable, i.e., the ratio of the labor supply of returning migrants and non-migrants. In order to be able to learn something from the data, it is required that the sampling error does not exceed the variance that remains after including all controls. Specifically, the following equations give an estimate of the bias:

$$\text{percent bias} = (1-\tau)\,\frac{\bar{p}\,(1-\bar{p})/\bar{n}}{(1-R^2)\,\sigma_p^2} \tag{11}$$

$\tau = 0.1$ is the fraction of the total population included in the sample, in this paper it is 10%. $\bar{p} \approx 0.0077169$ refers to the average size of the explanatory variable, and it is approximately 0.0077. σ_p^2 refers to the variance of $\bar{p}$, and has a value of 0.0000326. $\bar{n} \approx 38278.12$ is the average sample size of each education-experience cell. Finally, $1-R^2$ is the percent of the total variation in the ratio of labor supplies that remains after including controls. For columns 2,3 and 4 of Table

4, this value is 0.5717, 0.275 and 0.1343, respectively. Using equation 11 gives a percent bias that ranges from a low 1.3% to a high of 4.1%.

In sum, the analysis is valid for WLS estimates and suggests that the bias is rather small.

Modeling assumptions

Results in Table 4 are robust to modeling assumptions regarding relative productivities, $\theta^{m}_{ext}/\theta^{nm}_{ext}$. Previous literature (Borjas et al., 2012) has pointed that for the U.S. results are somewhat sensitive to varying assumptions about relative productivities between natives and immigrants. A point to note is that additional fixed effects have the undesired consequence of throwing away important variation and increasing standard errors (Ottaviano and Peri, 2012), consequently, highly saturated models might be uninformative and cannot reject the hypothesis that there is imperfect substitution. In contrast to U.S. based evidence, results in Table 4 are robust to varying assumption regarding relative productivities.

Missclasification and bias in the estimate of $1/\sigma_m$

In contrast to existing literature(Borjas, 2003; Ottaviano and Peri, 2012; Manacorda et al., 2012), where data sources identify foreign workers, in this study all workers are Mexican nationals. Fortunately, the Mexican census asks if a worker was living abroad five years ago. A limitation is that returnees that returned 6 or more years cannot to be identified, and misclassification is likely.

To address this concern, it is possible to drop observations from states with high migration rates to exploit the fact that historically most migrants originate in a few states in Mexico (Hanson, 2007). Dropping observations from high migration states eliminates most of the misclassification between returnees and non-migrants. The reason is that low migration states have a smaller stock of returnees with 6 or more years of education. Table A6 in the appendix shows estimates using this strategy. Point estimates for the combined sample and male-only sample are precisely estimated and confirm the hypothesis that returnees and non-migrants are imperfect substitutes. Results are not very different from those using the full sample, suggesting that classification it not a major concern.

Grouping workers into alternative education clusters

Additional robustness evidence is shown in Table A7. In Table A7, workers are grouped into 5 educational attainment cells. Point estimates are not very different from those using 6 cells. Results using 5 educational attainment cells are also robust to sub-samples and distinct assumptions about relative productivities. Overall, results in this section are robust to sample selections, clustering assumptions and different assumptions about the technology parameters of the structural model.

Non-parametric standard errors

A potential concern is that the large sample theory used to derive clustered standard errors might provide a poor approximation. The key problem is only having 48 clusters. To address this concern, I generate non-parametric standard errors through the wild bootstrap method proposed by Davidson and MacKinnon (2010) and Roodman et al. (2019). The method is known to work well under heteroscedasticity of unknown form, with finite samples even when the IVs are weak.

Figure A2 in the appendix displays the distribution with the confidence intervals for the IV estimates of the male sample in Table 4. Panel (a) of figure A2 displays the 95% confidence interval for column 5 of panel C. Point estimates range from -0.47 to -0.19. Panel (b) and (c) display 90% confidence intervals for columns 6 and 7, and the confidence intervals are (-0.34, -0.07) and (-0.25,-0.11), respectively. Lastly, panel (d) displays the 95% confidence interval for column 8 of panel C in Table 4, and it is (-1.15,-0.054). Using non-parametric confidence intervals perfectly agrees with the previous results.

New research by Abadie et al. (2020) shows that when working with the entire population, as I do in this paper, uncertainty is best viewed as design-based as opposed to emanating from sampling variation. That is, the study uses the entire population, but lack of knowledge of the counterfactual generates uncertainty. Abadie et al. show that in general, standard errors derived from the usual infinite-population sampling-based approach, as I did in this paper, are conservative.

In sum, the non-parametric approach agrees with the previous results, although these are likely to be conservative estimates.

4.3 Imperfect substitution is consistent with migrants acquiring human capital

Results are consistent with migrants acquiring human capital abroad if migrants earn more after returning, and they become imperfect substitutes. In this section, I document that wage gains and imperfect substitution only emerge upon returning to Mexico: results are not driven by unobserved heterogeneity before leaving Mexico, miss-classification of first-time migrants, potential econometric issues, positive selection upon returning from the U.S. or relocation to high-wage locations or agglomerations.

Testing for imperfect substitution: pre-migration

A possibility regarding the results on imperfect substitutability is that imperfect substitution emerges before workers migrate. In other words, there is a dimension of heterogeneity that is always present among migrants. To test for this possibility, the empirical approach uses data from ENE and ENOE to capture out-flows of migrants. ENE and ENOE have a panel structure that captures wages and other demographic characteristics of workers before they migrate. Since ENE and ENOE are yearly data, the IV in this section uses data from the CPS to match the periodicity.

Non-parametric evidence from Figure 2 lends support to the human capital result. Both panels capture the ratio of log wages and log relative supplies. Panel (a) displays the ratios for returning migrants and non-migrants, and panel b) displays the same ratio for migrants before they leave and non-migrants. First, notice that the fitted line in panel (b) is horizontal, whereas the fitted line in panel (a) is downward sloping. In light of the stylized model, a horizontal line means that the elasticity of substitution is infinite, and a downward sloping line means that the same elasticity is less than infinite. In other words, in panel (a), migrants are imperfect substitutes to the non-migrant population when they return. In contrast, in panel b), before migrants leave, they are perfect substitutes for the non-migrant population. Another feature observable in panel (a) is that for the ratios of returnees to non-migrants the fitted line is above zero. This implies that returning migrants earn more relative to the non-migrant population. But the same exercise for migrants before they leave generates a line that is not distinguishable from zero. Thus, pre-migration, these workers earn about the same.

Table A2 presents the relative labor supply and wages of non-migrant workers and migrants before they depart. The first point to note in Table A2, consistent with a human capital model, is that before migrants leave, they do not consistently out-earn non-migrants. This result stands in stark contrast with the patterns that emerge from Table 3, in which, at every educational attainment level, returning migrants out-earn non-migrant workers.This result suggests that the human capital that migrants acquire abroad is valued in the home-country labor market.

The third part of the analysis uses the structural model to test for imperfect substitution between non-migrant workers and migrants before they leave. To set up the test, I empirically estimate equation 5 using data from ENE and ENOE. If $1/\sigma_m = 0$, it implies that before the migration event, the model collapses to a simpler version without imperfect substitutability between migrants and non-migrant workers.

Table A8 in the appendix presents the results of the estimates of equation 5. Columns 1 through 4 of panel A show that the slope is zero in every model. That is, regardless of the empirical specification, before workers migrate, it is not possible to reject the null hypothesis that they are perfect substitutes. Point estimates are smaller in absolute value compared to results in Table 4, and sometimes the sign is wrong (positive). Moving to panel B and C shows a similar erratic pattern that point to perfect substitutability before migrants leave.

IV estimates do not reject the null hypothesis that migrants before they leave and non-migrants are perfect substitutes. Columns 5 and 6 of panel A do not reject the null hypothesis of perfect sustitutability. Columns 6 and 7 also give supporting evidence, although judging from the first stage F-statistic of excluded instruments, results should be taken with caution. For columns 6 and 8 of panel A, the F-statistic suggests a bias of roughly 30 percent. But this would not overturn the absence of imperfect substitution.

For the female sample in panel B and for the male sample in panel C, the F-statistic is also low. However, for the models 6 and 8 of panel B and 5 and 6 of panel C of Table A8, where F-statistics surpass the weak instrument threshold, all results fail to reject the null hypothesis of no imperfect substitution.

In sum, non-parametric, unprocessed data, WLS and IV estimate support the idea that migrants only become imperfect substitutes after the migration episode.[31]

Most out-migrants are first time migrants

Out-flows are a combination of first-time migrants and repeat migrants. If outflows are primarily composed of first-time migrants, then we know that the absence of imperfect substitution is driven by this population. In contrast, if most migrants are repeat migrants, it would require a reappraisal of results in Table A8.

Using MxFLS, it is possible to identify every person that ever migrated before 2002 and see if they migrated to the U.S. again between 2002 and 2006. The advantage of using this time-frame is that the MxFLS team published an exhaustive list of anyone who migrated between 2002 and 2006.

Based on the MxFLS, the weighted sample suggests that 23.6 percent of migrants are repeat migrants. The unweighted sample suggests that repeat migrants comprise 13.7 percent of out-flows.

Therefore, results are primarily driven by first-time migrants, lending support to the view that first-time migrants and non-migrants are perfect substitutes.

[31] Evaluating the potential bias based on Aydemir and Borjas (2011) suggests that the bias is also small, ranging from 2% to 5% for different specifications.

Analysis of WLS estimates

Although most out-migrants are first-time migrants, it is crucial to understand how miss-classification translates to point estimates. In appendix B, section 8.1, I derive the effect of miss-classification on the final estimate $\hat{\frac{1}{\sigma}}$. The result is derived under the null hypothesis of perfect substitution between first-time migrants and non-migrants.

Under the null hypothesis, the impact of miss-classification is very small, generating point estimates of roughly -0.005. The alternative hypothesis would generate much larger point estimates that should align with results in Table 4. Moreover, the test has enough power (above 0.8) to detect the effect. Therefore, directly testing for the null $\frac{1}{\sigma} = 0$ is a valid approach to test for imperfect substitution between first-time migrants and non-migrants.

Migrant selection is not driving the results

Existing literature using ENE (Fernandez-Huertas, 2011) and panel data from MxFLS (Kaestner and Malamud, 2014) noted that out-migrants tend to be negatively selected in terms of earnings.[32] What is remarkable is that return migrants, a population drawn from a negatively selected pool, can overturn this pattern.

Evidence from the U.S. (Lubotsky, 2007) and Italy (Bartolucci et al., 2018) suggests that relative to migrants at the destination, returnees are negatively selected from the income, wage and observed skill distribution .[33] In other words, the literature shows that return migrants are also negatively selected from the pool of migrants.

In sum, the literature suggests that it is highly unlikely that the observed wage profile of returning migrants is due to a compositional effect.

[32]Previous literature found that Mexican migrants were positively selected (Chiquiar and Hanson, 2005), but the differences between this and most recent results can be attributed to differences in data sources. Chiquiar and Hanson use data that undercount undocumented migrants.

[33]But might be positively selected on unobserved dimensions.

Return-migrants' relocation within Mexico does not drive the results

The remaining issue is the possibility that return-migrants disproportionally relocate to high-wage states in Mexico, potentially generating the observed wage gains. Table A9 estimates the wage premium of return-migrants under a Mincer wage specification. The models control for age and experience.

Including state-fixed effects in column 1 of Table A9 effectively estimates the premium by comparing non-migrants and return-migrants within a state. In column 3, including a locality size effect excludes the possibility that migrants move to highly dense areas that offer a wage premium.

Alternatively, data from *Encuesta Nacional de la Dinámica Demográfica* (ENADID) can be used to estimate how many return-migrants move to new locations upon returning to Mexico. According to ENADID, 72.4% of migrants return to the location where they were born. Similarly, 80.4% of the total number of migrants who did not return[34] departed from the state where they were born. Under the assumption that migrants that departed from the state where they were born and those who did not behave similarly, these figures suggest that roughly 10% of return-migrants move to a different state upon return. This small percent cannot generate the observed wage gains. In sum, the evidence presented in this section is consistent with a human capital model.[35]

[34]According to the Mexican Census, between 80.5% and 82.1% of the non-migrant population between 1990 and 2015 continued to live in the state where they were born. The figure is not different from that of the migrant population that did not return. These numbers imply that roughly 8% of returning migrants move to a different state.

[35]There is empirical evidence for Mexico and Europe (De Coulon and Piracha, 2005; Gang et al., 2000; Barrett and Goggin, 2010; Barrett and O'Connell, 2001; Reinhold and Thom, 2013; Zahniser and Greenwood, 1998; Li, 2018) and theoretical arguments (Borjas and Bratsberg, 1996; Dustmann and Weiss, 2007; Dustmann et al., 2011; Dos Santos and Postel-Vinay, 2003; Mayr and Peri, 2009) supporting the link between experience abroad and human capital accumulation. But this evidence has not addressed the link with imperfect substitution.

FIG. 3. –The y-axis is the log of monthly real wages in 2015 Mexican pesos. The x-axis is the labor composite required by the model. Dots are proportional to the sample size used to obtain the average wage in each education-experience-year cell.

4.4 Inverse of the elasticity of substitution across experience groups: $1/\sigma_x$

From the first stage, I obtained all the parameters required by the model to generate the labor composite. The dependent variable in this section is the mean of the log wage of each education-experience cluster in a given year, and the key explanatory variable is the labor supply.

Figure 3 is the scatter plot of wages on the y-axis and the labor composite on the x-axis, adjusted by education, experience, and other effects required by the model. Each dot represents an education-by-experience cluster in a given year. There is a clear downward slope, implying that as labor supply increases, wages decrease.

Table 6 presents estimates of the elasticity of substitution across experience groups, $1/\sigma_x$. $1/\sigma_x$ is precisely estimated and negative, regardless of the sub-population or assumptions about the technology parameters. The key difference between the columns in Table 6 is the assumption regarding the technology parameters. Equation 6 requires the inclusion of year and education by year controls. The models do this non-parametrically by including fixed effects. Columns 1 and 4 assume that the technology parameter θ_{ext} is a constant. Columns 2 and 5 assume θ_{ext} can be described by experience-education specific trends. Lastly, column 3 and 6 assume that θ_{ext} can be capture non-parametrically by an education-by-experience fixed effect.

Implied elasticities of substitution for the full sample in columns 1 through 3 range from 4.3 to 9. For the female and male only sample results are similar.

IV estimates in columns 4 through 6 in panel A imply elasticities of substitution that range from 1.4 through 9. In panel B and C of Table 6, results are similar. In general, IV estimates move in the expected direction, i.e., point estimates are larger in absolute value.

Monte Carlo simulations and uncertainty of the labor composite

The labor composite used to estimate $1/\sigma_x$ comes from equation 4. Thus, the key regressor carries uncertainty that emanates from estimates of θ^k_{ext} for $k = n, nm$. To explore the consequence of this uncertainty on the estimate of $1/\sigma_x$, I run a Monte Carlo simulation. Specifically, to $\hat{\theta}^k_{ext}$ the experiment adds randomness from a uniform distribution $u \sim [-0.3, 0.3]$. Since $\hat{\theta}^k_{ext}$ ranges from 0.3 to 0.53, adding draws from $u \sim [-0.3, 0.3]$ ensures that $\hat{\theta}^k_{ext}$ is still positive and that values are centered around $\hat{\theta}^k_{ext}$.

Figure A3 in the appendix displays the distribution of $\hat{\frac{1}{\sigma_x}}$. Figure (a) assumes that θ_{ext} is a constant. Figure (b) assumes that θ_{ext} can be discomposed into education-experience specific trends. Lastly, figure (c) assumes that θ_{ext} can be discomposed into education-experience fixed effects. The emerging distributions are skewed, suggesting confidence intervals that are clearly negative, but favor the possibility of having estimates of $1/\sigma_x$ with larger absolute values.

4.5 Inverse of the elasticity of substitution across educational attainment groups: $1/\sigma_e$

For this result, the model uses the average of the log wage of each educational attainment group as the dependent variable. Labor supply is the log of the labor composite required by the model.

Table 7 presents the results. Taking the combined point estimates of all the models, they imply an elasticity of substitution across educational attainment groups that ranges from 0.6 to

Table 6
Inverse of the elasticity of substitution between experience groups

Panel A: Full Sample	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
All	-0.23***	-0.027	-0.11***	-0.71***	-0.11***	-0.39***
	(0.03)	(0.03)	(0.03)	(0.23)	(0.04)	(0.06)
N	192	192	192	192	192	192
F-statistic				5.70	17.8	14.7
Year FE	YES	YES	YES	YES	YES	YES
Education FE × Year FE	YES	YES	YES	YES	YES	YES
Education FE × Experience FE	NO	NO	YES	NO	NO	YES
Experience × Education Trends	NO	YES	NO	NO	YES	NO

Panel B: Females	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Females	-0.21***	-0.028	-0.13***	-0.67***	0.0045	-0.32***
	(0.02)	(0.03)	(0.03)	(0.23)	(0.05)	(0.05)
N	188	188	188	188	188	188
F-statistic				4.93	17.5	14.4
Year FE	YES	YES	YES	YES	YES	YES
Education FE × Year FE	YES	YES	YES	YES	YES	YES
Education FE × Experience FE	NO	NO	YES	NO	NO	YES
Experience × Education Trends	NO	YES	NO	NO	YES	NO

Panel C: Males	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Males	-0.23***	-0.004	-0.086**	-0.78***	-0.14***	-0.38***
	(0.03)	(0.03)	(0.03)	(0.28)	(0.05)	(0.07)
N	192	192	192	192	192	192
F-statistic				5.21	17.7	14.6
Year FE	YES	YES	YES	YES	YES	YES
Education FE × Year FE	YES	YES	YES	YES	YES	YES
Education FE × Experience FE	NO	NO	YES	NO	NO	YES
Experience × Education Trends	NO	YES	NO	NO	YES	NO

NOTES. -The dependent variable is the average log wage of each education-experience skill group. Wages include full time workers, who are not self-employed, and not enrolled in school. The models are weighted by the size of the labor supply. Robust standard errors clustered over education-experience cells are reported in parenthesis. Labor supply is labor composite suggested by the model, and it includes the self-employed, males, and females. Only years 1990, 2000, 2010, and 2015, are included, since only in these years migrants can be identified.. F-statistic refers to the effective F-statistic of excluded instruments Olea and Pflueger (2013). * p <0.1, ** p<0.05, *** p<0.01.

12.5. The three specifications tested in this paper include a year effects, year and education fixed effects and education splines. The models in column 5 and 6 in panel A and B are not statistically significant, but I'll show in the next subsection that this is in part due to data limitations.

The sample restriction generates small point estimates

A main limitation of estimates in Table 7 is that to strictly follow the stylized theoretical model many observations have to be dropped. Specifically, any year in which migrants cannot be identified is not part of the estimation. This leaves the years 1990, 2000, 2010, and 2015. Since there are 6 educational attainment groups, results only use 24 observations.

Table A10 artificially imposes the same sample restriction needed to generate the model parameters in order to explore the impact on point estimates. Comparing each panel of Table A10 and Table 7 shows perfect agreement. That is, WLS and IV point estimates generate the same results. This implies that all the parameters needed to generate the labor composite of equations 3 and 4 mean very little for actual point estimates.

Since using the labor composite or the labor supply generates the same result, Table A11 explores the impact of relaxing the sample restriction. First, columns 1 through 3 in every panel use all the available data, and this includes the years 1960, 1970 and 1995 in which returning migrants cannot be identified. The most prominent feature is that all results are precisely estimated, and the magnitude of the inverse elasticity is larger in absolute value. Columns 4 through 6 in each panel of Table A10 use the IV. Years 1960 and 1970 are not included because the IV is only available after 1980. In line with previous results, the inverse elasticity is precisely estimated and larger in absolute value.

5 Simulation Results

Factor demand theory (Hamermesh, 1996) provides guidance for the factor price elasticities:

Table 7
Inverse of the elasticity of substitution between educational attainment groups

Panel A: Full Sample	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
All	-0.35***	-0.056**	0.0018	-1.64***	-0.082	-0.079
	(0.10)	(0.02)	(0.02)	(0.58)	(0.05)	(0.05)
N	24	24	24	24	24	24
F-statistic				5.40	20.7	22.5
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES
Panel B: Females	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Females	-0.36***	-0.055***	-0.024	-1.93***	0.017	0.013
	(0.10)	(0.02)	(0.02)	(0.73)	(0.09)	(0.09)
N	24	24	24	24	24	24
F-statistic				4.86	16.6	18.0
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES
Panel C: Males	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Males	-0.37***	-0.060**	0.0090	-1.64***	-0.12***	-0.12***
	(0.10)	(0.03)	(0.03)	(0.57)	(0.05)	(0.05)
N	24	24	24	24	24	24
F-statistic				5.65	20.7	22.4
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES

NOTES. -The dependent variable is the average log wage of each educational attainment group group. Wages include full time workers, who are not self-employed, and not enrolled in school. The models are weighted by the size of the labor supply. Robust standard errors clustered over education-experience cells are reported in parenthesis. Labor supply is labor composite suggested by the model, and it includes the self-employed, males, and females. Only years 1990, 2000, 2010, and 2015, are included, since only in these years migrants can be identified.. F-statistic refers to the effective F-statistic of excluded instruments Olea and Pflueger (2013). * p <0.1, ** p<0.05, *** p<0.01.

$$\varepsilon_{ik} = \frac{d \log w_i}{d \log L_k} = \gamma_k \frac{Q_{ik} Q}{Q_i Q_k} \tag{12}$$

ε_{ik} is the factor price elasticity, i.e., how wages of labor-type i would change if labor-type k changes. γ_k is the share of income going to factor k. Q is the output or production function, and Q_i is the partial derivative with respect to factor i. The wage elasticity of returnees (non-migrants) with the same education (e) and experience (x) with respect to other returnees (non-migrants) is:

$$\varepsilon^m_{ex,ex} = \frac{1}{\sigma_{KL}} s^m_{ex} + \left(\frac{1}{\sigma_e} - \frac{1}{\sigma_{KL}}\right)\frac{s^m_{ex}}{s_L} + \left(\frac{1}{\sigma_x} - \frac{1}{\sigma_e}\right)\frac{s^m_{ex}}{s_e} + \left(\frac{1}{\sigma_M} - \frac{1}{\sigma_X}\right)\frac{s^m_{ex}}{s_{ex}} - \frac{1}{\sigma_m} \tag{13}$$

s^m_{ex} is the share of income accruing to returnees with experience x and education e. s_L is the share of income accruing to labor, roughly 67%, according to IMF data. s_e is the share of income accruing to workers with education e. σ_e is the elasticity of substitution between labor and capital. There is a second order effect experienced by workers that share the same education and experience (who may or may not be returnees):

$$\varepsilon_{ex,ex} = \frac{1}{\sigma_{KL}} s^m_{ex} + \left(\frac{1}{\sigma_E} - \frac{1}{\sigma_{KL}}\right)\frac{s^m_{ex}}{s_L} + \left(\frac{1}{\sigma_x} - \frac{1}{\sigma_E}\right)\frac{s^m_{ex}}{s_e} + \left(\frac{1}{\sigma_M} - \frac{1}{\sigma_X}\right)\frac{s^m_{ex}}{s_{ex}} \tag{14}$$

There are two additional indirect effects caused by workers with the same education but different experience, and another effect by workers with different education and any experience:

$$\varepsilon_{emx,emx'} = \frac{1}{\sigma_{KL}} s^m_{ex'} + \left(\frac{1}{\sigma_E} - \frac{1}{\sigma_{KL}}\right)\frac{s^m_{ex'}}{s_L} + \left(\frac{1}{\sigma_x} - \frac{1}{\sigma_E}\right)\frac{s^m_{ex'}}{s_e} \tag{15}$$

$$\varepsilon_{ex,e'x'} = \frac{1}{\sigma_{KL}} s^m_{e'} + \left(\frac{1}{\sigma_E} - \frac{1}{\sigma_{KL}}\right)\frac{s^m_{e'}}{s_L} \tag{16}$$

With the set of price elasticities, in the short-run, i.e, when capital is fixed, the effect of a returnee-induced supply shock on returnees' wages is:

$$\triangle \ln w_{ex}^{m} = \varepsilon_{ex,ex}^{m} m_{ex}^{m} + \sum_{j=x} \varepsilon_{ex,ej} m_{ej} + \sum_{y \neq e} \sum_{j} \varepsilon_{ex,ij} m_{ij} \tag{17}$$

m_{ij} is the returnee-induced percent change in labor-type cell i, j. For non-migrants the returnee-induced shock in the short-run is:

$$\triangle \ln w_{ex}^{nm} = \sum_{j=x} \varepsilon_{ex,ej} m_{ej} + \sum_{y \neq e} \sum_{j} \varepsilon_{ex,ij} m_{ij} \tag{18}$$

Similarly, in the long-run, when capital is optimally adjusted, the effect on returnees' wages is:

$$\triangle \ln w_{exm} = \frac{s_k}{\sigma_{kl}} \tilde{K} + \varepsilon_{ex,ex}^{m} m_{ex}^{m} + \sum_{j} \varepsilon_{ex,ej} m_{ej} + \sum_{y \neq e} \sum_{j} \varepsilon_{ex,ij} m_{ij} \tag{19}$$

For non-migrants in the long-run:

$$\triangle \ln w_{ex}^{nm} = \frac{s_k}{\sigma_{kl}} \tilde{K} + \sum_{j} \varepsilon_{ex,ej} m_{ej} + \sum_{y \neq e} \sum_{j} \varepsilon_{ex,ij} m_{ij} \tag{20}$$

s_k is capital's share of income. $\tilde{K}$ is the percent change in the capital stock induced by the labor supply shock.[36] The simulation assumes that the size of the labor force in Mexico is held constant at 2010 levels. Since the Mexican census is likely to undercount return migrants if they returned more than five years ago, I use the Mexican Family Life Survey to count workers who spent more than a year abroad, but have returned no more than ten years ago. To calculate how workers would be distributed between the education-experience clusters, I use the U.S. census and the American Community Survey, and take the empirical distribution of Mexican workers currently residing in the U.S. A limitation is that official U.S. data sources undercount illegal immigrants (Warren and Passel, 1987). In addition, illegal immigrants tend to be younger and less educated than the Mexican workers observed in the data. The combined effect is reducing the true impact

[36]The change in the capital stock is $\tilde{K} = \sum_i s_i m_i / s_L$. γ_L is labor's share of income. m_i is the percent change in the labor supply of group i.

of migration at the lower tail of the educational attainment distribution.

Simulations use the following point estimates for the inverse of the elasticities: for the inverse of the elasticity between returnees and non-migrants, the value is 0.096, which is the average of point estimates for the full sample in columns 6, 7 and 8 of panel A of Table 4; for the inverse elasticity across experience groups it is 0.25, which is the average of columns 5 and 6 of panel A in Table 6; and for the elasticity across educational attainment groups, it is 0.165, which is the average of columns 5 and 6 of panel A in Table A11. Inverse elasticities are assumed to be normally distributed with standard deviations that are averaged over the same columns. All models use the full sample (males and females) and group labor-types into 6 education and 8 experience clusters. There is only one point estimate of 0.9 (Shah, 1992) for the elasticity of substitution between capital and labor. To capture the uncertainty regarding σ_{kl} in the simulation, σ_{kl} has a uniform distribution ranging from 0.7 to 1.1.

5.1 The asymmetric impact of 1 million returning migrants and 1 million out-migrants

The key advantage of the simulation is to facilitate the analysis of either a first-time migrant induced shock or a return migrant shock. In practice, out-flows combine first-time migrants and repeat migrants. Thus, from observed data it would not be possible to disentangle the impact of either group. A 1 million returnee-induced shock is roughly the size of the number of Mexicans that returned to Mexico from the U.S. around the Great Recession.

To understand the heterogeneity of out and return flows, Table 8 and 9 present the wage impact of a 1 million returnee-induced increase in the labor supply and a 1 million outmigrant-induced decrease in the labor supply.[37] The first column of Table 8 and 9 contrast the impacts of these shocks on returnees' wages. In Table 8, in the short-run, out-migration produces wage gains across the board for the returnee population. The gains are modest ranging from 0.56% to 0.63%, since out-migrants and returnees are imperfect substitutes. In contrast, a returnee-induced

[37] 1 million is approximately the number of Mexicans returning to Mexico between 2007 and 2012.

Table 8
Effect of 1 million out-migrants on wages in Mexico

	Short-run			Long-run		
	(1)	(2)	(3)	(4)	(5)	(6)
	Returnees	Non-Migrants	All	Returnees	Non-Migrants	All
Less than Primary	0.56	1.13	1.12	-0.59	-0.02	-0.03
	(0.21)	(0.18)	(0.19)	(0.16)	(0.12)	(0.12)
Less than Secondary	0.63	1.63	1.61	-0.52	0.48	0.46
	(0.34)	(0.29)	(0.30)	(0.29)	(0.24)	(0.24)
Less than High School	0.63	1.12	1.11	-0.51	-0.03	-0.04
	(0.20)	(0.18)	(0.18)	(0.12)	(0.09)	(0.09)
High School	0.62	2.49	2.46	-0.53	1.35	1.31
	(0.60)	(0.53)	(0.53)	(0.56)	(0.48)	(0.48)
Some College	0.51	2.02	2.00	-0.64	0.87	0.85
	(0.52)	(0.47)	(0.47)	(0.49)	(0.44)	(0.44)
College	0.49	0.85	0.85	-0.65	-0.30	-0.30
	(0.16)	(0.15)	(0.15)	(0.09)	(0.05)	(0.05)

NOTES. –This table shows the impact on wages of an increase of 1 million returning migrant workers. The empirical distribution to calculate shocks to specific labor-types is obtained from the U.S. census and the American Community Survey. In addition to the sample restrictions previously mentioned, workers must be born in Mexico. Standard errors are reported in parenthesis.

shock in Table 9 presents economically important losses for the returnee population. The wage losses range from .88% to 3.87%. Moving to the impacts in the long-run, the asymmetries are more evident. In column 4 of Table 9, the wage impact of the returnee-induced labor supply shock is consistently negative and sizable. On the other end, the out-migrant-induced shock has a smaller impact, that is almost uniformly distributed across educational attainment groups. In sum, the impacts go in the expected direction, but the magnitudes are different and there are asymmetries.

The effects on the wages of non-migrants are asymmetric, too. In column 2 of Table 9, a one million returnee-induced shock causes wage declines of not more than 0.02%. In the long-run, in column 5 of Table 9, the effects are positive, but of little economic importance. Moving to the out-migrant-induced shock, wage changes range from a low of 0.85% to a high of 2.49%. Despite the fact that the shocks are of the same size, magnitudes of the impacts are very different. In the long run, only college-educated and the less educated workers experience a small wage decline.

Heterogeneity can only be captured when imperfect substitution between returnees and non-

Table 9
Effect of 1 million returning migrants on wages in Mexico

	Short-run			Long-run		
	(1)	(2)	(3)	(4)	(5)	(6)
	Returnees	Non-Migrants	All	Returnees	Non-Migrants	All
Less than Primary	-1.18	-0.01	0.00	-1.16	0.01	0.00
	(0.51)	(0.00)	(0.00)	(0.51)	(0.00)	(0.00)
Less than Secondary	-1.46	-0.01	0.00	-1.44	0.01	0.00
	(0.62)	(0.01)	(0.00)	(0.62)	(0.01)	(0.00)
Less than High School	-0.88	-0.01	0.00	-0.86	0.01	0.00
	(0.38)	(0.00)	(0.00)	(0.38)	(0.00)	(0.00)
High School	-3.42	-0.02	-0.03	-3.40	0.00	-0.02
	(1.50)	(0.01)	(0.01)	(1.50)	(0.01)	(0.01)
Some College	-3.87	-0.01	0.00	-3.85	0.01	0.00
	(1.72)	(0.01)	(0.00)	(1.72)	(0.01)	(0.00)
College	-0.66	-0.01	-0.01	-0.64	0.01	-0.01
	(0.29)	(0.00)	(0.00)	(0.29)	(0.00)	(0.00)

NOTES. –This table shows the impact on wages of an increase of 1 million returning migrant workers. The empirical distribution to calculate shocks to specific labor-types is obtained from the U.S. census and the American Community Survey. In addition to the sample restrictions previously mentioned, workers must be born in Mexico. Standard errors are reported in parenthesis.

migrants is explicitly modeled. This result also speaks to the fact that it is other returnees that are the most exposed to a returnee-induced labor supply shock. The same shock has a small impact on non-migrants in the short run. In contrast, in the long run, when capital adjusts, gains are concentrated across all educational attainment groups.

Total effects in the short (column 3) and the long run (column 6) in Tables 8 and 9 are small because a one million labor supply shock is small relative to the size of the Mexican labor market. But the final results show that the overall impact of a returnee-induced labor supply shock would have an economic unimportant effect on the total population. Although the impact on returnees would be significant. In contrast, an out-migrant induced shock of the same size would have important effects on the overall economy.

5.1.1 The cumulative impact of 7.6 million emigrants to the U.S. has been asymmetric

Table 10 presents the simulation of the cumulative impact of migration to the U.S. on wages in Mexico. 7.6 million is roughly the Mexican-born population that is part of the labor force and

Table 10
Effect of 7.6 million out-migrants on wages in Mexico

	Short-run			Long-run		
	(1)	(2)	(3)	(4)	(5)	(6)
	Returnees	Non-Migrants	All	Returnees	Non-Migrants	All
Less than Primary	4.27	8.59	8.53	-4.46	-0.14	-0.25
	(0.60)	(0.59)	(0.59)	(0.38)	(0.37)	(0.37)
Less than Secondary	4.75	12.40	12.24	-3.98	3.68	3.48
	(0.60)	(0.59)	(0.59)	(0.38)	(0.37)	(0.37)
Less than High School	4.82	8.51	8.45	-3.91	-0.22	-0.30
	(0.60)	(0.59)	(0.59)	(0.38)	(0.37)	(0.37)
High School	4.70	18.96	18.72	-4.02	10.23	9.99
	(0.60)	(0.59)	(0.59)	(0.38)	(0.37)	(0.37)
Some College	3.89	15.33	15.21	-4.84	6.60	6.48
	(0.60)	(0.59)	(0.59)	(0.38)	(0.37)	(0.37)
College	3.75	6.48	6.44	-4.98	-2.25	-2.28
	(0.60)	(0.59)	(0.59)	(0.38)	(0.37)	(0.37)

NOTES. –This table shows the impact on wages of a decrease of 7.6 million workers due to migration. The empirical distribution to calculate shocks to specific labor-types is obtained from the U.S. census the American Community Survey. Standard errors are reported in parenthesis.

lives in the U.S. In this exercise, the empirical distribution of education and potential experience is taken from the U.S. Census and American Community Survey; by looking at the age and education distribution of the Mexican born population in the U.S., I construct an empirical distribution of skill and experience that is used for the labor supply shock. The first thing to notice in columns one and two of Table 10, is that the effects are considerable larger for non-migrants than for returnees. Moving to the combined effect, they are somewhere between the effect on non-migrants and returnees because these are weighted averages.

In the long-run, once capital reaches a new optimal level to match the current labor supply, the impact on wages is asymmetric, too. Returnees' wages experience a decrease across the board. Non-migrants experience somewhat different qualitative results, and the impacts are bigger. In the long-run, non-migrant high school graduates gain 10.23 percent, while workers with some college education gain 6.6 percent. At the top and bottom of the educational attainment distribution, college graduates workers and workers with less than primary education experience wage losses.

Previous literature (Aydemir and Borjas, 2007) found that the long-term impacts of emigration from Mexico to the U.S. between 1970 and 2000 increased wages for workers with high school and some college education by 7.5 and 5.4 percent, respectively. They also find a decrease of 3.1 percent in wages of college educated workers, and roughly 1 percent for the least educated workers. I used recent data, updated demographics to 2010 and estimated the impact of a shock that is similar in size to the Mexican-born population living in the U.S. in 2010.[38] By finding imperfect substitution between returnees and non-migrants, this paper shows that there are clear heterogenous effects. Out-migration has a direct impact on non-migrants. In fact, the impacts of out-migration and return-migration are asymmetric.

6 Conclusions

This research was motivated by the observation of the continued decline in Mexico–U.S. migration, an increase in the number of returning migrants from the U.S. to Mexico and the rapid pace at which immigration policy is currently changing in the U.S. These facts prompt the question of whether or not returnees and non-migrants are perfect substitutes in order to fully understand the consequences of the new migration patterns.

This paper tests whether returnees and non-migrants are perfect substitutes. Previous literature closely related to this paper (Cortes, 2008; Card, 2009; Ottaviano and Peri, 2012; Manacorda et al., 2012; LaLonde and Topel, 1991) documented a small, but imperfect degree of substitutability between natives and immigrants in the U.S. and the U.K. Adding to existing literature, this research shows that there is a small degree of imperfect substitutability between workers that remain in Mexico and workers that return from abroad. For the preferred estimates, the implied elasticity of substitution between returnees and non-migrants ranges from 4 to 10.

Imperfect substitution generates asymmetries in the impact of returnee-induced and out-migrant-induced shocks. Simulations show that other returnees suffer important wage reduc-

[38]The population that meets the sample restrictions is roughly 7.6 million according to the Current Population Survey.

tions as a consequence of return migration. In contrast, the least and most educated workers who remained in Mexico experience small gains that are not economically important due to complementarities with returning workers. Workers with high school or some college education would experience small losses because the proportion of returning migrants is large in these educational attainment cells. An out-migrant-induced shock of the same magnitude concentrates the impacts on non-migrants.

This paper also revisits the impact of long-term out-migration on wages in Mexico. In regard to the impact of out-migration, wage gains are concentrated on workers with high school and some college education. But it contributes to existing literature by pointing that it is non-migrants who capitalize such gains. In contrast, returnees experience losses across the entire educational attainment distribution due to an unfavorable capital adjustment.

Imperfect substitutability is broadly consistent with a human capital model, in which workers not only acquire skills that directly increase their wages upon returning to Mexico, but these skills also make them imperfect substitutes. Three important questions for future research are whether it is possible to replicate the results, e.g., if temporary work visas can generate the gains in wages and skills observed in the Mexican lab, and if this is the case, under what conditions. Thirdly, what is it that migrants learn that generates the change. In this paper, I rule out several possibilities, including: out-migrant selection, return-migrant selection, differential assimilation to the Mexican labor market upon returning, relocation to high-wage locations and several econometric issues.

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7 Appendix A

Table A1
Local average treatment interpretation of the IV

	(1)	(2)	(3)	(4)	(5)
Instrument	-86.6***	-135.4*	-85.5***	-87.7***	-109.7***
	(10.75)	(68.62)	(20.61)	(19.55)	(17.10)
Educational Attainment Groups in Sample					
Less Than Primary	YES	NO	YES	YES	NO
Primary but Not Secondary	YES	NO	YES	YES	YES
Secondary But Not High School	YES	NO	YES	YES	YES
High School	YES	YES	NO	YES	YES
Some College	YES	YES	NO	YES	YES
College Graduates	YES	YES	NO	NO	NO
N	191	95	96	159	127
R-Square	0.74	0.72	0.73	0.74	0.80

NOTE. –This table displays the first-stage regression of the IV on the ratio of labor supplies. Each column includes a different sub-sample. The educational attainment groups in the sample shows which workers are included in the sample. All models include education-by-experience and year fixed effects. Robust standard errors clustered over education-experience in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A2

Top 25 Occupations for non-migrants and returnees from 1990 to 2010

Type of Occupation	Non-migrants		Returnees	
	Share	Rank	Share	Rank
Merchants in business establishments	12.14%	1	9.32%	3
Home and personal care workers	10.40%	2	6.29%	4
Workers in the extraction and construction of buildings	9.01%	3	10.57%	2
Workers in farming activities	6.84%	4	13.17%	1
Operators of industrial machinery, assemblers, drivers and transport drivers	4.62%	5	3.14%	10
Workers in protection and surveillance services	4.17%	6	2.70%	13
In-store sales employees	3.67%	7	4.58%	6
Transport and mobile machinery drivers	3.64%	8	5.10%	5
Drivers and driver assistants moving machinery and means of transport	3.12%	9	1.62%	17
Domestic, cleaning, ironing and other cleaning workers	2.72%	10	2.15%	14
Workers in food preparation and service in establishments	2.67%	11	3.50%	8
Assemblers and assemblers of tools, machinery, metal and electronic products	2.63%	12	1.09%	26
Specialists in economic and administrative sciences, social sciences, humanities and the arts	2.61%	13	2.78%	12
Workers in fishing, forestry, hunting and similar activities	2.57%	14	1.71%	16
Workers of the Navy, Army and Air Force	2.43%	15	1.07%	27
Managers and managers in production, technology and transportation	2.33%	16	1.44%	20
Directors and managers in financial, administrative and social services	2.20%	17	1.20%	24
Craftsmen and workers in the processing and processing of metal products	2.12%	18	2.06%	15
Officials and senior officials from the public, private and social sectors	2.02%	19	1.19%	25
Auxiliaries and technicians in exact sciences, biological, engineering, informatics and telecommunications	1.93%	20	2.94%	11
Secretaries, captains, cashiers and file control and transportation workers	1.91%	21	1.36%	21
Support workers in mining, construction and industry	1.40%	22	3.79%	7
Teachers and teaching specialists	1.28%	23	0.78%	29
Craftsmen and workers in the production of wood products, paper, textiles and leather	1.12%	24	1.61%	18
Street vendors	1.06%	25	1.53%	19

NOTE. –The share refers to the percent of workers in an industry. Rank refers to how important is an industry relative to total employment.

Table A3

Relative wages and labor supply: Pre-migration

	Education	Relative Supply (%)	Relative Wages (%)
Year 2000:			
	Less than primary	1.31	134.47
	Primary education but not secondary	1.45	122.17
	Secondary education but not high school	0.94	98.59
	High school graduate	0.53	77.30
	Some college	0.39	100.56
	College graduate	0.39	104.09
Year 2005:			
	Less than primary	1.01	140.13
	Primary education but not secondary	1.13	97.19
	Secondary education but not high school	0.56	92.89
	High school graduate	0.43	102.90
	Some college	0.20	117.79
	College graduate	0.21	89.87
Year 2010:			
	Less than primary	0.33	108.07
	Primary education but not secondary	0.26	113.19
	Secondary education but not high school	0.22	94.26
	High school graduate	0.14	128.90
	Some college	0.12	111.91
	College graduate	0.05	141.30
Year 2015:			
	Less than primary	0.17%	89.93
	Primary education but not secondary	0.18%	109.51
	Secondary education but not high school	0.17%	95.77
	High school graduate	0.11%	70.06
	Some college	0.12%	113.73
	College graduate	0.10%	63.00

NOTE. –Table A1 uses ENE and ENOE data. Relative supply is the ratio of the labor supply of returnee to non-migrant workers. Relative wage is the ratio of their wages. Workers' wages are recorded before they migrate.

Table A4
Assimilation test

	(1)	(2)	(3)	(4)	(5)	(6)	(8)
Return Migrant	0.048**	0.042	0.064	0.057	0.11**	0.11**	0.088**
	(0.02)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Return Migrant × Experience		0.00022	-0.00042	-0.00026			
		(0.002)	(0.002)	(0.002)			
Return Migrant × Education					-0.0070	-0.0072	-0.0043
					(0.004)	(0.004)	(0.004)
N	4430	4430	4430	4430	4430	4430	4430
R-Square	0.29	0.29	0.28	0.27	0.29	0.28	0.27
Education FE	YES	YES	YES	NO	YES	NO	NO
Experience FE	YES	YES	NO	NO	YES	YES	NO
Education + Education^2	NO	NO	NO	YES	NO	YES	YES
Experience + Experience^2	NO	NO	YES	YES	NO	NO	YES

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

NOTE. –This table displays mincerian wage equations using individual level data from the Mexican Family Life Survey. Robust standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5
Dissimilarity of occupation across educational attainment groups using data from MxFLS

Educational Attainment Group	Dissimilarity Within Educational Attainment Group
Elementary	4.31%
Secondary	7.83%
High school	4.56%
Open high school	.73%
Normal basic	1.03%
College	3.96%
Graduate	.74%
Open secondary	.95%
Without instruction	.28%
Preschool or kinder	.071%
Mean	2.45%

NOTE. – This table displays the Duncan Dissimilarity Index using data from MxFLS. The MxFLS offers the advantage of recording the full migration history of a nationally representative sample, but this is a snapshot of the year 2000.

Table A6
Inverse of the elasticity of substitution between returning migrants and non-migrants in low migration states

Panel A: Full Sample

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.090***	-0.055***	-0.058**	-0.087***	-0.25***	-0.061***	-0.13**	-0.10
	(0.01)	(0.01)	(0.03)	(0.03)	(0.05)	(0.02)	(0.06)	(0.08)
N	223	223	223	223	191	191	191	191
F-statistic					100.8	17.4	51.9	9.78
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

Panel B: Females

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.13***	-0.081***	-0.036	-0.066	-0.26***	-0.13***	-0.13	0.14
	(0.02)	(0.03)	(0.06)	(0.09)	(0.07)	(0.04)	(0.09)	(0.24)
N	197	197	197	197	183	183	183	183
F-statistic					57.2	52.7	44.3	23.4
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

Panel C: Males

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.01***	-0.063***	-0.051	-0.11***	-0.28***	-0.12***	-0.14**	-0.22***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.05)	(0.02)	(0.06)	(0.07)
N	217	217	217	217	190	190	190	190
F-statistic					105.6	14.0	45.1	8.29
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

NOTE. –Wage calculations include full time workers, who are not self-employed, and not enrolled in school. Labor supply includes the total count of workers (males and females), and the self-employed. The model is weighted by the inverse of the variance of the dependent variable. Robust standard errors are reported in parenthesis, clustered over education-experience cells. F-statistics refers to the excluded instruments. Table includes the years 1990, 1995, 2000, 2010, and 2015 but the IV results exclude the year 1995 due to data availability. * p <0.1, ** p<0.05, *** p<0.01.

Table A7
Inverse of the elasticity of substitution between returning migrants and non-migrants using 5 educational attainment groups

Panel A: Full Sample

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.089***	-0.058***	-0.056*	-0.092***	-0.28***	-0.075***	-0.13***	-0.14*
	(0.01)	(0.02)	(0.03)	(0.03)	(0.06)	(0.03)	(0.05)	(0.08)
N	186	186	186	186	159	159	159	159
F-statistic					70.2	30.4	55.6	10.6
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

Panel B: Females

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.13***	-0.086***	-0.045	-0.096	-0.31***	-0.15**	-0.12	0.13
	(0.02)	(0.03)	(0.05)	(0.09)	(0.08)	(0.06)	(0.10)	(0.25)
N	165	165	165	165	153	153	153	153
F-statistic					42.1	61.1	49.9	23.1
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

Panel C: Males

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.098***	-0.066***	-0.049	-0.11***	-0.31***	-0.12***	-0.13**	-0.26***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.06)	(0.03)	(0.06)	(0.08)
N	180	180	180	180	158	158	158	158
F-statistic					72.5	25.8	47.3	8.91
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

NOTE. –Wage calculations include full time workers, who are not self-employed, and not enrolled in school. Labor supply includes the total count of workers (males and females), and the self-employed. The model is weighted by the inverse of the variance of the dependent variable. Robust standard errors are reported in parenthesis, clustered over education-experience cells. F-statistics refers to the excluded instruments. Table includes the years 1990, 1995, 2000, 2010, and 2015 but the IV results exclude the year 1995 due to data availability. * p <0.1, ** p<0.05, *** p<0.01.

Table A8
Pre-migration: Inverse of the elasticity of substitution between out-migrants and non-migrants

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	0.00025	-0.041	-0.024	-0.020	-0.024	0.034	-0.36	0.23
	(0.05)	(0.06)	(0.04)	(0.04)	(0.08)	(0.10)	(0.41)	(0.23)
N	688	688	688	688	688	688	688	688
F-statistic					12.0	25.3	3.56	4.81
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

Panel B: Females

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.035	0.097	0.059	-0.0058	-0.71	-0.54	-1.18	0.14
	(0.05)	(0.08)	(0.05)	(0.07)	(0.84)	(0.50)	(2.67)	(0.12)
N	618	618	618	618	618	618	618	618
F-statistic					0.71	3.89	0.33	12.3
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

Panel C: Males

	WLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	0.028	0.14^{**}	0.013	-0.037	0.020	0.16^{***}	-0.33	-0.23
	(0.03)	(0.06)	(0.03)	(0.03)	(0.05)	(0.05)	(0.40)	(0.35)
N	604	604	604	604	604	604	604	604
F-statistic					11.8	9.68	1.46	1.52
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Education × Year FE	NO	YES	NO	YES	NO	YES	NO	YES
Education × Experience FE	NO	NO	YES	YES	NO	NO	YES	YES

NOTE. –Wage calculations include full time workers, who are not self-employed, and not enrolled in school. Labor supply includes the total count of workers (males and females), and the self-employed. The model is weighted by the inverse of the variance of the dependent variable. Robust standard errors are reported in parenthesis, clustered over education-experience cells. F-statistic refers to the excluded instruments. The table uses ENE for the years 2000 through 2004 and ENOE for the years 2005 through 2015. The IV uses data from the CPS to match the periodicity of ENE and ENOE. * p <0.1, ** p<0.05, *** p<0.01.

Table A9

Return-migrants' wage premium

	(1)	(2)	(3)
Dependent Variable	Log of Real Monthly Income		
Return-Migrant	0.177***	0.181***	0.211***
	(0.003)	(0.003)	(0.003)
Constant	7.443***	7.113***	7.412***
	(0.004)	(0.007)	(0.004)
Observations	6,895,896	6,895,896	6,800,270
R-squared	0.232	0.238	0.252
State FE	x	x	x
Year FE		x	x
Locality Size FE			x

NOTE. –This table estimates returning migrants' wage premium under alternative specifications. All specifications control for age and education. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A10
Inverse of the elasticity of substitution between educational attainment groups with sample restrictions

Panel A: Full Sample	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
All	-0.35***	-0.090***	-0.090***	-1.64***	-0.082	-0.079
	(0.10)	(0.02)	(0.02)	(0.58)	(0.05)	(0.05)
N	24	24	24	24	24	24
F-statistic				5.40	20.7	22.5
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES

Panel B: Females	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Females	-0.36***	-0.074*	-0.074*	-1.93***	0.017	0.013
	(0.10)	(0.04)	(0.04)	(0.73)	(0.09)	(0.09)
N	24	24	24	24	24	24
F-statistic				4.86	16.6	18.0
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES

Panel C: Males	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Males	-0.37***	-0.11***	-0.11***	-1.64***	-0.12***	-0.12***
	(0.10)	(0.02)	(0.02)	(0.57)	(0.05)	(0.05)
N	24	24	24	24	24	24
F-statistic				5.65	20.7	22.4
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES

NOTES. - The dependent variable is the average log wage of each education. Wage calculations include males and females, working full time, who are not self-employed, and not enrolled in school. Labor supply includes the total count of workers (males and females), and the self-employed. The model is weighted by employment. Robust standard errors are reported in parenthesis, clustered over education-experience cells. It includes the years 1990, 2000, 2010, and 2015. * p <0.1, ** p<0.05, *** p<0.01.

Table A11
Inverse of the elasticity of substitution between educational attainment groups

Panel A: Full Sample	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
All	-0.42***	-0.22***	-0.22***	-2.29**	-0.16***	-0.17***
	(0.05)	(0.02)	(0.02)	(1.10)	(0.04)	(0.04)
N	42	42	42	30	30	30
F-statistic				3.13	25.7	28.5
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES

Panel B: Females	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Females	-0.44***	-0.21***	-0.21***	-2.51**	-0.071	-0.078
	(0.05)	(0.02)	(0.02)	(1.20)	(0.06)	(0.06)
N	42	42	42	30	30	30
F-statistic				3.13	25.7	28.5
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES

Panel C: Males	WLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Males	-0.44***	-0.24***	-0.24***	-2.34**	-0.19***	-0.20***
	(0.06)	(0.02)	(0.02)	(1.13)	(0.04)	(0.04)
N	42	42	42	30	30	30
F-statistic				3.13	25.7	28.5
Year FE	YES	YES	YES	YES	YES	YES
Education Fixed Effects	YES	YES	NO	YES	YES	NO
Education Splines	NO	YES	YES	NO	YES	YES

NOTES. -The dependent variable is the average log wage of each educational attainment group group. Wages include full time workers, who are not self-employed, and not enrolled in school. The models are weighted by the size of the labor supply. Robust standard errors clustered over education-experience cells are reported in parenthesis. Labor supply is natural logarithm, and it includes the self-employed, males, and females. Only years 1990, 2000, 2010, and 2015, are included, since only in these years migrants can be identified.. F-statistic refers to the effective F-statistic of excluded instruments Olea and Pflueger (2013). * p <0.1, ** p<0.05, *** p<0.01.

Table A12
Elasticity of substitution across educational attainment groups using ENE and ENOE

	Elasticity of substitution across educational attainment groups					
	-0.24***	-0.22***	-0.25***	-0.21***	-0.21***	-0.22***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
No Trends	x			x		
No Weights		x			x	
Education Specific Trends			x			x
Number of Cells		110			132	

NOTES. - The dependent variable is the average wage of each education. Wage calculations include males and females, working full time, who are not self-employed, and not enrolled in school. Labor supply includes the total count of workers (males and females), and the self-employed. The model is weighted by employment. Robust standard errors are reported in parenthesis, clustered over education-experience cells. It includes every year since 1995 to 2016. * p <0.1, ** p<0.05, *** p<0.01.

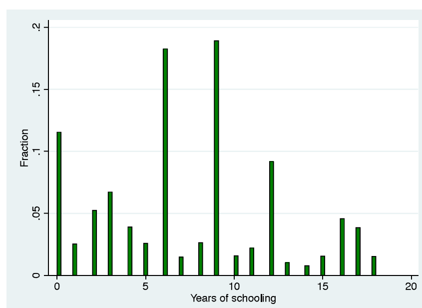


FIG. A1. –Empirical distribution of educational attainment

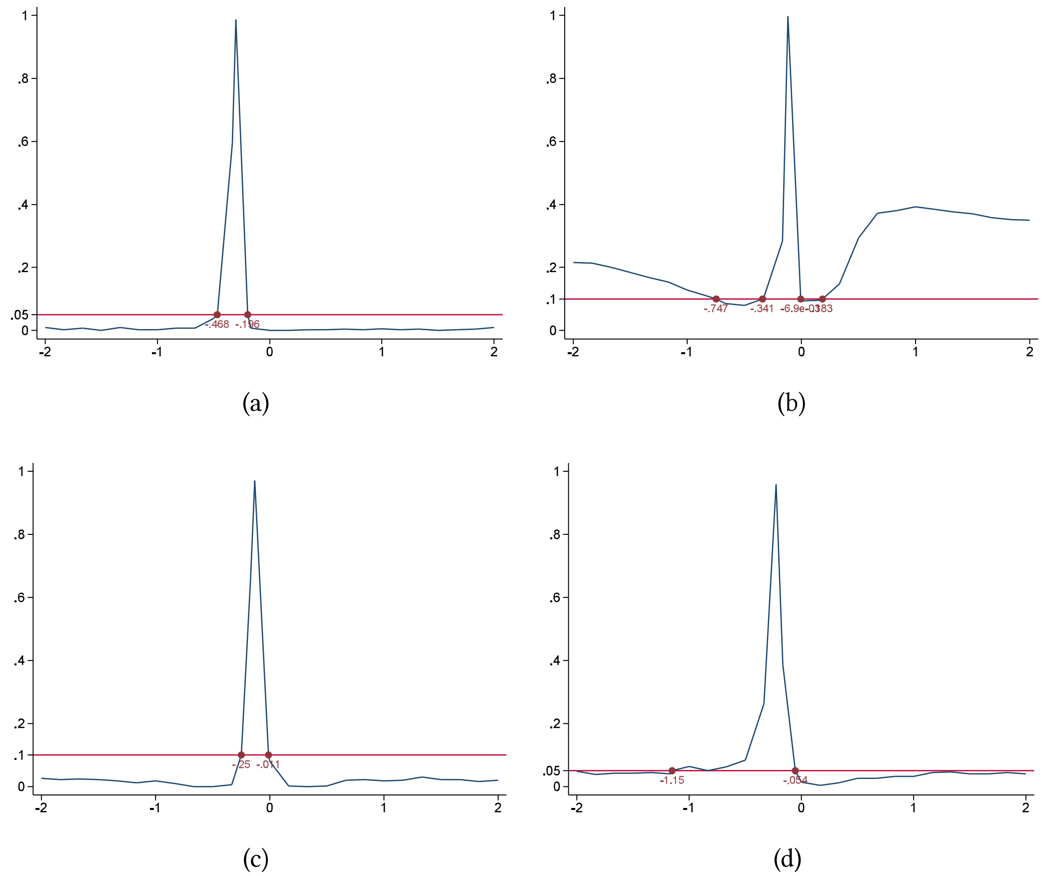
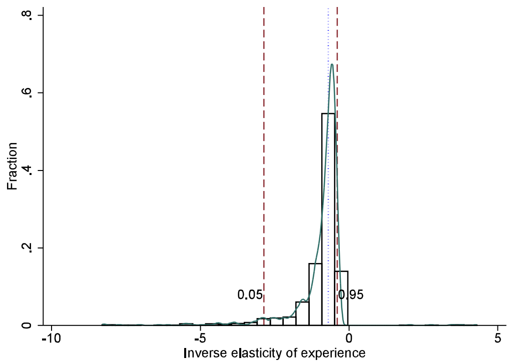
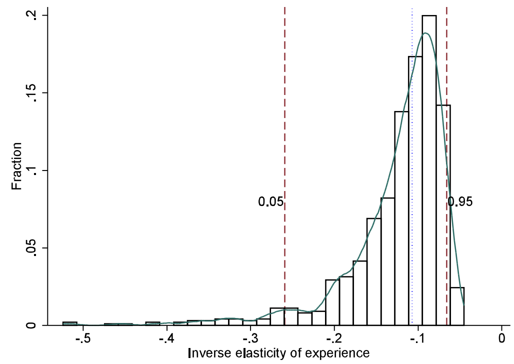


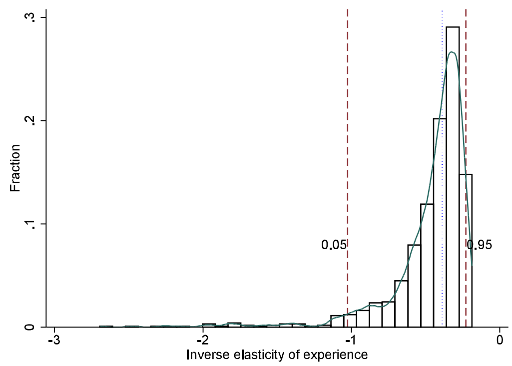
FIG. A2. –Wild bootstrap standard errors of the elasticity of substitution for the male population. The figures correspond to panel C of Table 4. Figure (a) corresponds with column 5. Figure (b) corresponds with column 6. Figure (c) corresponds with column 7. Figure (d) corresponds with column 8. Figure (b) and (c) present 90% confidence intervals. Figure (a) and (d) present 95% confidence intervals.



(a)



(b)



(c)

FIG. A3. –Monte Carlo simulation of estimates of the elasticity of substitution of experience. The dotted red lines represents the 95% confidence interval, and the dotted blue line refers to the median. Figure (a) corresponds to column 4 of panel A of Table 6. Figure (b) corresponds to column 5 of panel A of Table 6. Figure (c) corresponds to column 6 of panel A of Table 6.

8 Appendix B

8.1 Partial regression analysis: perfect substitution between first-time migrants and non-migrants

This section presents the consequence of miss-classification on the estimate of the inverse of the elasticity of substitution between first-time migrants and non-migrants. In particular, under the null hypothesis of perfect substitution between first-time migrants and non-migrants, it's easy to show that the null requires $\frac{1}{\sigma} = 0$

A partial regression of the log ratio of supplies on wages generates an estimate of the inverse of the elasticity of substitution that equals:

$$\frac{\hat{1}}{\sigma} = \left(\sum_i \hat{r}_i y_i\right) / \left(\sum_i (\hat{r}_i)^2\right)$$

$\hat{r}_i$ is the residual the regression of log ratio of labor supplies on all fixed effects. Notice that initially, the key explanatory variable is

$$log\left(FT/NM + RM/NM\right) = log\left(FT/NM\left[1 + RM/FM\right]\right)$$

where FT/NM refers to the ratio of first time migrants to non-migrants, and RM/NM is the ratio of repeat migrants to non-migrants. RM/NM is present because using ENE and ENOE, it is not possible to identify repeat migrants. Therefore,

$$log\left(FT/NM + RM/NM\right) = log\left(FT/NM\right) + log\left(1 + RM/FM\right)$$

A residual approach, that is, regressing each term in the above equation on all the fixed effects, to get the residual of $log\left(FT/NM\right)$, which I denote

$$\hat{r}_{iF}$$

Similarly, for the term $log\left(1 + RM/FM\right)$, I denote the residual as

$$\hat{r}_{iR}$$

Therefore, $\hat{r}_i$ equals:

$$\hat{r}_i = \hat{r}_{iF} + \hat{r}_{iR}$$

Thus, the estimate of the inverse of the elasticity is

$$\frac{\hat{1}}{\sigma} = \left(\sum_i (\hat{r}_{iF} + \hat{r}_{iR}) y_i \right) / \left(\sum_i (\hat{r}_i)^2 \right)$$

Therefore, $\frac{\hat{1}}{\sigma}$ can be split into two terms:

$$\frac{\hat{1}}{\sigma} = \underbrace{\sum_i \hat{r}_{iF} y_i / \left(\sum_i (\hat{r}_i)^2 \right)}_{\text{this is zero in expectation}} + \sum_i \hat{r}_{iR} y_i / \left(\sum_i (\hat{r}_i)^2 \right)$$

Under the null hypothesis, that is, that first-time migrants and non-migrants are perfect substitutes, the first term is zero. Therefore, $\frac{\hat{1}}{\sigma}$ reduces to

$$\frac{\hat{1}}{\sigma} = \sum_i \hat{r}_{iR} y_i / \sum_i (\hat{r}_i)^2$$

Using data from the Mexican Census and Mexican Population Counts, I obtained estimates of

$$\sum_i \hat{r}_{iR} y_i = -0.008482$$

$$\sum_i (\hat{r}_i)^2 = 1.69$$

Therefore, under the null with miss-classification

$$\frac{\hat{1}}{\sigma} \approx -0.005$$

In practice, the above discussion implies that under the null, the point estimate $\frac{1}{\sigma} \approx 0$, but the alternative implies $\frac{1}{\sigma} \neq 0$

8.2 Optimal weights for equation 5

The dependent variable is the difference between the mean of the log wage:

$$\overline{\ln w_{iexmy}} - \overline{\ln w_{iexnmy}} = \frac{1}{n}\sum \ln w_{iexmy} - \frac{1}{k}\sum \ln w_{jexnmy}$$

where m refers to migrants and nm to non-migrants. n is the number of migrants in the sample and k the number of non-migrants. Assuming independence across observations and using the variance operator

$$Var\left(\frac{1}{n}\sum \ln w_{iexmy} - \frac{1}{k}\sum \ln w_{jexnmy}\right) = \frac{n \cdot Var\left(\ln w_{iexmy}\right)}{n^2} + \frac{k \cdot Var\left(\ln w_{kexnmy}\right)}{k^2} \implies$$

$$Var\left(\frac{1}{n}\sum \ln w_{iexmy} - \frac{1}{k}\sum \ln w_{jexnmy}\right) = \frac{kVar\left(\ln w_{iexmy}\right) + nVar\left(\ln w_{kexnmy}\right)}{nk} \implies$$

Therefore, the optimal analytical weights are:

$$Var^{-1}\left(\frac{1}{n}\sum \ln w_{iexmy} - \frac{1}{k}\sum \ln w_{jexnmy}\right) = \frac{nk}{kVar\left(\ln w_{iexmy}\right) + nVar\left(\ln w_{kexnmy}\right)}$$