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Abstract

We study the effect of return migration from the U.S. to Mexico on the economies of Mexican cities. In principle, returnees increase the local labor supply and therefore put pressure on wages and employment rates of locals. However, having worked in the technologically more advanced US economy, they may also possess skills that complement the skills of local workers or even bring in new organizational and technological know-how that leads to productivity improvements in Mexico. Using an instrument based on involuntary return migration due to deportation by US authorities, we find evidence in support of both effects. Returnees affect wages of locals in different ways: whereas workers who share the returnees' occupations experience a fall in wages, workers in other occupations see their wages rise. However, the latter, positive, effect is easily overlooked, because it is highly localized: it only affects coworkers within the same city-industry cell. Moreover, both, positive and negative, wage effects are transitory and eventually disappear. In contrast, by raising the employment levels of the industry in which they find jobs, returnees permanently alter a city's industry composition.

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Introduction

Migration between the U.S. and Mexico has received ample attention in academic and public debates. These debates have mostly focused on whether migration from Mexico to the U.S. helps or hurts U.S. workers, and, to a lesser extent, on whether or not this migration represents a brain-drain to the Mexican economy. However, we know little about what happens when Mexican emigrées return home. This is surprising, given that, with an average of about 200,000 yearly returnees in the first decade of the 21st century, return migration is an important aspect of the account of migration between Mexico and the U.S.. A priori, it is unclear how these return migrants affect the Mexican economy. On the one hand, Mexican returnees tend to have low levels of formal education, even relative to the wider Mexican population. Their return may therefore simply expand the supply of low-skill labor and depress the wages of locals with similarly low skill levels. On the other hand, having worked in the U.S. may have provided the returnees with new skills and with valuable knowledge of advanced organizational and technological processes. In that case, local workers would benefit from returnees through skill complementarities and knowledge spillovers. We study the balance of these effects, by estimating how return migration affects wage and employment growth in Mexican cities. To ensure that the estimated effects have a causal interpretation, we use an identification strategy that exploits information on Mexican immigrants who left the U.S. involuntarily, being deported by U.S. authorities.

Much of the debate about whether immigrants help or hurt locals revolves around the question of whether these immigrants are substitutes or complements to local workers (Dustmann et al., 2016). If immigrants have the same skills as locals, negative substitution effects will dominate. If immigrants have different skills than locals, locals will see their wages and employment opportunities increase. Both effects essentially operate through immigrants' increasing the local supply of certain skills. In line with this, most existing literature has classified locals and immigrants in terms of their levels of education and occupational work experience (Borjas, 2003), sometimes further subdividing these categories by country of birth (Ottaviano and Peri, 2012).

However, such skill-based taxonomies are poorly suited to capture the effects of knowledge spillovers if they involve an understanding of production processes or of organizational routines. We argue that such knowledge spillovers will mainly be felt within the productive unit in which an immigrant – or, in our case, a returnee – finds employment. We will proxy these productive units by city-industry cells. The reasoning behind this is that workers acquire knowledge about production processes and organizational routines related to the industries in which they worked in the U.S.. Such industry-specific knowledge can be used to upgrade the technology of the same industry in Mexico. These knowledge spillovers would therefore boost productivity and expand the demand for labor in the industry, as well as temporarily raise wages.

We interpret our empirical findings in the context of a stylized two-by-two-by-two model that combines the industry-specific elements of a Heckscher-Ohlin world with the notion of spatial equilibrium. In this setting, migration has short and long term effects on local workers. The short term effects manifest themselves in wage disparities that provide the incentive for workers to move between industries – as in a Heckscher-Ohlin model – or between cities – as in spatial equilibrium models. In the long run, however, such wage disparities will dissipate. In contrast, technological spillovers and Rybczynski effects will lead to permanent shifts in employment, changing a city's industry mix (as suggested in Dustmann and Glitz, 2015).

The empirical analysis must confront the fact that the volume of migration flows will be highly endogenous to wages and employment growth: returnees may impact wages and employment in a city-industry cell, but they may also be attracted by them. To deal with such concerns, we construct an instrument that uses data on Mexican migrants who return to Mexico involuntarily. In particular, we predict industry-specific return-migration flows into Mexican cities by crossing the US industry of work with the Mexican place of birth for a sample of migrants that were deported from the U.S..

Another major concern that has been raised in the migration literature is that estimating the effects of migration by comparing regions with, to regions without, immigrants may underestimate migration effects if workers can freely relocate within the country. In that case, observations taken from regions that receive no or few international immigrants offer poor counterfactuals to those that do, because their economies may attract workers who move out of more affected regions to cope with the influx of immigrants (Borjas et al., 1996; Card, 2001). Such internal mobility will disperse the effects of immigration across worker categories and locations, diluting them to an extent that they become hard to identify.

We argue that such concerns can – at least partially – be addressed by studying temporal variations in the effects of migration. The rationale for this is that the problem of improper spatial counterfactuals is most salient when identifying long-run effects. After all, the mobility of workers that restores a local labor market equilibrium in the long run requires that some observable wage differences appear for workers to exploit in the short run.

Our empirical analysis corroborates these considerations. We find that wages of locals respond to an influx of return migrants. However, these effects are transitory, peaking after two to three years and fading out within five years. Moreover, the full range of effects is only visible when we divide workers into city-industry-occupation cells. Locals experience wage decreases when returnees enter their city-industry in the local workers' own occupations. In contrast, locals experience wage increases when returnees enter other occupations in the city-industry. These latter, positive, effects would have remained hidden, had we studied local wages in city-occupation cells instead of city-industry-occupation cells. This shows the importance of isolating the productive units in which immigrants find work.

In contrast to the temporary wage effects of returnees, their employment effects are permanent. Local industries that receive return migrants grow for about three years, after which their employment more or less plateaus. This growth is expressed in terms of jobs for local workers, i.e., excluding the jobs of the returnees themselves. Therefore, the permanent effect on employment means that return migrants create new employment opportunities. Notably, the increase in employment exceeds what we would expect from the Rybczynski effect in a standard Heckscher-Ohlin model. The Rybczynski effect is a pure skill-supply effect: it only depends on the extent to which the supply of the type of labor that an industry uses intensively increases. To quantify this effect, we construct an indicator of how suitable the inflow of return migrants to a city is for each industry in terms of the inflow's occupational composition. As expected, this variable is associated with an employment expansion in the local industry. However, its inclusion in our regression models does not meaningfully decrease the estimated effect of return migration. We therefore conclude that the estimated employment effects are unlikely to be fully – or even largely – attributable to the increase in skill supply that return migrants represent. Instead, and in conjunction with the observed positive wage effects, our estimates suggest that return migrants may help diffuse valuable know-how from the U.S. to Mexican cities.

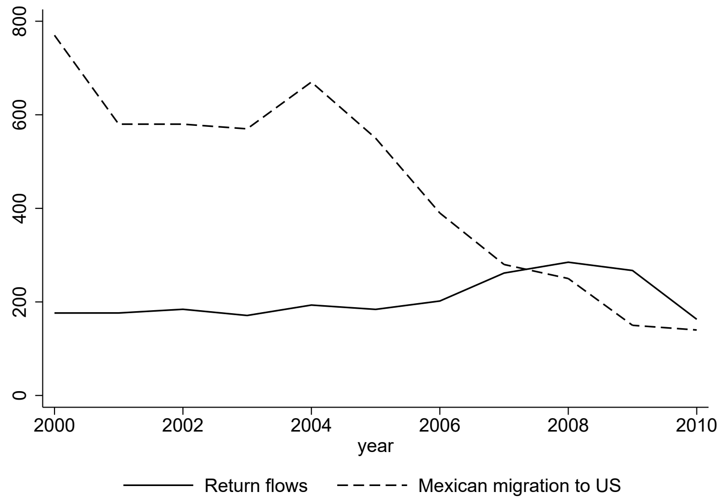
Our main findings are robust to a range of variations in how we quantify the intensity of return migration, to different sample definitions, and to using a different, independent, data set to measure wages and employment in city-industry-occupation cells. To gauge whether a local economy's unobserved attractiveness biases our estimates, we exploit information on workers who relocate within Mexico. When added as a covariate to control for a city-industry's attractiveness, we find virtually no changes in the estimated effects of return migration. When we use these internal migration flows as a placebo treatment, we fail to find any statistically significant evidence that the exogenous variation that our instrument isolates in these flows affects employment growth in the local industry.

Taken these findings together, our study provides important insights into a hitherto relatively neglected segment of one of the most visible migration corridors in the world: the return migration from the U.S. to Mexico. While a recent mimeo from Conover et al. (2018) analyzes the fall of net migration by focusing on the impact of workers not leaving Mexico, our work aims to specifically study the impact of returnees with experience in the U.S.. Understanding how Mexican returnees affect the local economies where they settle back complements a vast literature on migration between Mexico and the U.S. (e.g. Chiquiar and Hanson, 2005; Borjas and Katz, 2007; Card and Lewis, 2007; Ambrosini and Peri, 2012; Reinhold and Thom, 2013; Clemens et al., 2018).

At a more general level, our study adds to the literature on the economics of migration. Historically, this literature has mostly focused on the flow from poor to rich countries, either asking whether or not migrants displace local workers in the recipient country (e.g. Borjas, 2003; Ottaviano and Peri, 2012) or how the potential brain drain undermines the development of the sending economy (Beine et al., 2008). More recently, scholars have stressed the potential for positive effects on the receiving country due to complementarities between locals and migrants or due to knowledge spillovers from highly skilled immigrants (Kerr and Lincoln, 2010; Moser et al., 2014; Hornung, 2014; Akcigit et al., 2017; Bahar and Rapoport, 2018). What this literature often neglects, is that, although migration flows may be imbalanced, very often, they do not just run in one direction (Saxenian, 2007). A substantial number of migrants eventually decide to return home. However, such return migration is qualitatively different from regular migration. First, return migrants face no language or cultural barriers when they return home. Second, the traditional understanding of high-skill migration poorly captures the knowledge about organizational and technological practices returnees acquire in advanced host economies. In line with this, and closely related to our study, return migrants have proven to be an important vector for knowledge transfer from technological advanced to lagging economies (Choudhury, 2015; Hausmann and Nedelkoska, 2018; Bahar et al., 2019). Accordingly, U.S. firms have different, more advanced organizational routines and work practices than their Mexican counterparts. Immigrants can absorb these routines through learning-by-doing or in-person communication with an instructor, which is required when the technology has a tacit component (Hornung, 2014). However, such learning need not be limited to high-skill migrants or high-tech industries, but can also be available to lower skilled workers in industries like agriculture and construction (Hausmann and Nedelkoska, 2018). We weigh the evidence in support of such learning effects in the return migration from the U.S. to Mexico within the context of a standard migration model.

Finally, it is important to note that our study only offers a partial analysis of the consequences of return migration from the U.S. to Mexico, leaving out important aspects for welfare considerations. First of all, we do not study the earnings losses of the returnees themselves. Based on data from IPUMS USA (Ruggles et al., 2019), wages of Mexican workers in the U.S. are higher than in Mexico by a factor two in real terms and by a factor four in nominal terms. Given that most return migrants do not return voluntarily, this difference in wages represents a substantial loss in income. Second of all, in 2015, the remittances that Mexican migrants who remained in the U.S. sent to their families in Mexico amounted to over 2% of Mexico's GDP (25B USD; The World Bank, 2016), about 2,000 USD per Mexican migrant. The income losses of Mexican returnees are therefore also felt by their families in Mexico, where they are further amplified by multiplier effects.

Figure 1: Migration flows (in Thousands)



Source: own elaboration using data from Pew Research and EMIF Norte.

1 Migration between Mexico and the United States

It is impossible to accurately chart a migration, the largest component of which aims to avoid being detected by the authorities. However, through triangulation of a variety of sources, we can get a clear enough picture of the general patterns that have unfolded over the past decade.

Figure 1 first shows the total migration flow from Mexico to the U.S., as well as the flow of Mexican returnees who moved in the opposite direction. The figure uses data from Pew Research for outflows and our estimate from the EMIF Norte[1] survey, for the return flows (see Appendix B.1 for details on the method we used). In the early 2000s, Mexican immigration in the U.S. was very high, with a yearly influx of over 700,000 Mexican nationals. However, this number steadily declined over the course of the decade to about 140,000 migrants in 2010. Meanwhile, the number of Mexican immigrants that returned home steadily increased. As a consequence, whereas in the early 2000s emigration from Mexico was about three times as high as the return migration to Mexico, by the end of the decade return migration had overtaken outmigration.

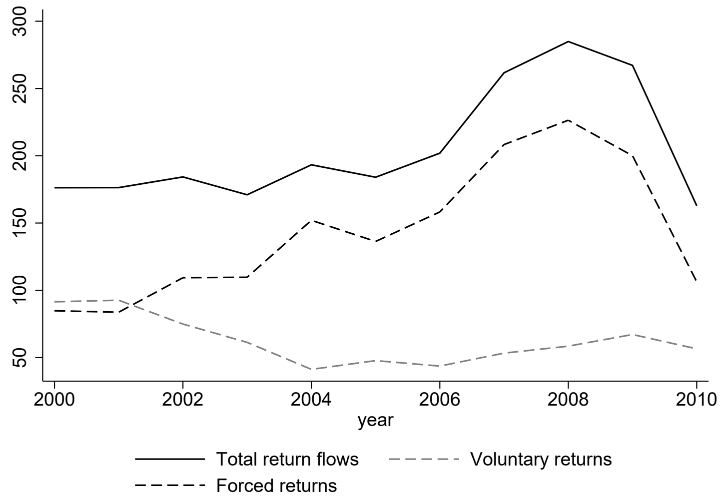
Figure 2 decomposes these return flows into voluntary returnees and deportees. After 2001, the number of forced returns increased, at which point they started dominating the return flows. To some extent, this simply reflects that the stock of Mexican immigrants in the U.S. had grown larger. However, a stricter law enforcement may as well have contributed to this trend.[2] However, with the financial crisis, net migration from Mexico to the U.S. has turned negative from 2008 on and forced return migration has fallen back to its 2000 level.

Figure 3 depicts the subnational origins and destinations of the flow of Mexican immigrants to the

[1] Encuesta sobre Migración en la Frontera Norte de México

[2] For instance, border enforcement tightened around 2006 (The Economist, 2014).

Figure 2: Return migration flows (in Thousands)



Source: own calculations using data from Pew Research and EMIF Norte.

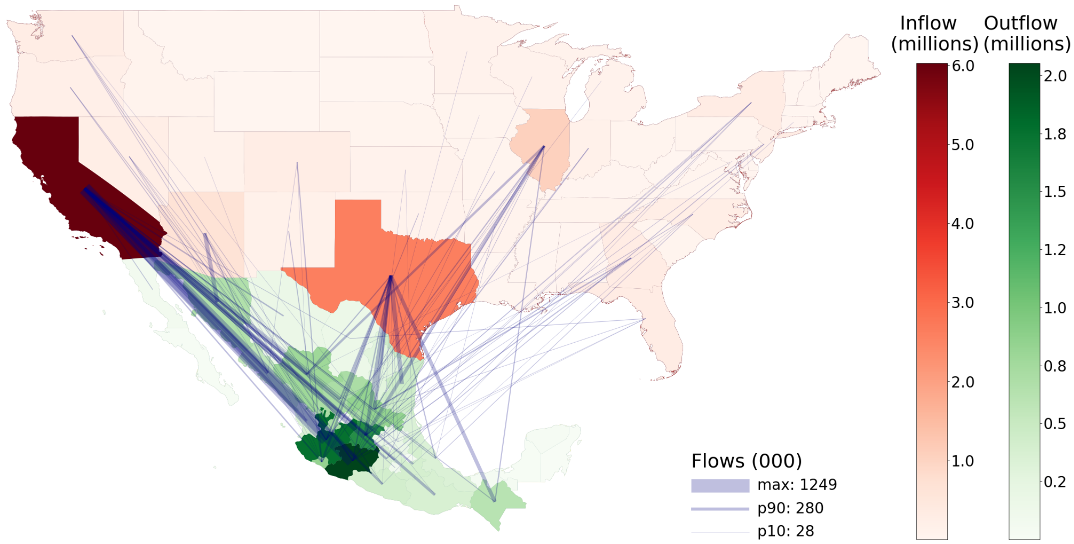
U.S. at the state level. To create this figure, we first estimate the number of migrants that leave each Mexican state. Unfortunately, no reliable data for this exist, given that a large share of this migration flow is undocumented. Instead, we rely on data collected by the Mexican border authorities in the EMIF Norte survey.[3] This survey collects data for the flow in the opposite direction: Mexicans in the U.S. who return to Mexico, be it voluntarily or involuntarily. Because the survey collects information on the location of birth in Mexico and the last location of residence in the U.S., we can use these data to roughly reconstruct the original flows of immigrants from Mexico to the U.S.. Next, we weight these flows by the number of Mexican workers in the U.S. as recorded in the American Community Survey (ACS).[4]

The destinations Mexican immigrants choose in the U.S. are highly geographically concentrated. The lion's share of immigrants is absorbed by two border states, California (41%) and Texas (18%). However, the immigration inflow has a wide range of origins in Mexico. Interestingly, most immigrants come from the center of Mexico, not from regions near the US border. For instance, about 14% of Mexican immigrants were born in Michoacán, a state immediately west of Mexico City. In contrast, the border region of Nuevo León, with roughly the same number of inhabitants, accounts for just 2% of Mexican immigrants in the U.S.. However, the migration flows between Mexican and US states are highly structured. For 16 out of Mexico's 32 states, over 50% of migrants choose the same US state as a destination. Although migrants tend to choose nearby destinations in the U.S., distance does not seem to be the main driver behind their decisions. For instance, in the southernmost regions, 70% of migrants from Oaxaca move to California, compared to 56% of migrants from Chiapas, who choose Texas as their destination and 44% of migrants from Tabasco, who move to Illinois.

[3] We use the surveys collected in the 5-year period 1999-2003.

[4] We access these data on IPUMS USA (Ruggles et al., 2019) for the years 2004-2006.

Figure 3: Subnational origins and destination of migration from Mexico to the U.S.



Source: own calculations using data from IPUMS US, the Mexican Census, and EMIF Norte.

A possible explanation for such spatial sorting is that migrants choose destinations in which their skills are in high demand. To explore this, we compare data on Mexicans living in the U.S. to data on Mexicans living in Mexico, using the ACS of 2005 for the U.S. and the ENOE[5] of 2005 for Mexico.

Table 1 explore what kind of jobs Mexicans hold in the U.S.. The column on the left reports the top 20 3-digit industries of the NAICS 2002 classification, in terms of an industry's Mexican employment share. The column on the right repeats this exercise using 3-digit SOC occupations. Mexican immigrants predominantly find work in agriculture, as well as in low-skill services and manufacturing industries. Although they sometimes have supervisory tasks, most the occupations they hold within these industries are found at the lower end of the skill spectrum.

To some extent, these specialization patterns simply reflect the average sociodemographic profile of these workers: Mexican immigrants are on average younger and less educated than the US population as a whole (Table 2). Moreover, the Mexican population in the US is not significantly younger and even somewhat more educated than the population at home.

We can explore whether the jobs that Mexican workers perform in the U.S. are mostly driven by the local demand for certain skills or by the skills these workers supply. To do so, let $LQ_{is}^{mig,US} = \frac{L_{is}^{mig,US}/L_{s}^{mig,US}}{L_{i}^{mig,US}/L^{mig,US}}$ be the location quotient (LQ) of Mexican workers in industry i in US state s, where $L_{is}^{mig,US}$ is the number of Mexican workers in the industry and omitted subscripts signify summations over the corresponding dimension. Similarly, $LQ_{is}^{loc,US}$ is the LQ of all other workers in the industry and $LQ_{is'}^{MEX}$ is the activity's LQ in Mexican state s'.

[5]Encuesta Nacional de Ocupación y Empleo. See section 3 and appendix B.2.

Table 1: Employment of Mexicans in the United States (IPUMS, 2005)

Industry of Mexicans in US	Share	Occupation of Mexicans in US	Share
Support Activities for Agriculture and Forestry	0.29	Agricultural Workers	0.40
Crop production	0.26	Supervisors, Farming, Fishing, and Forestry	0.23
Apparel Manufacturing	0.17	Grounds Maintenance Workers	0.22
Food Manufacturing	0.16	Food Processing Workers	0.19
Private Households	0.15	Textile, Apparel, and Furnishings Workers	0.16
Leather and Allied Product Manufacturing	0.14	Cooks and Food Preparation Workers	0.14
Furniture and Related Product Manufacturing	0.12	Building Cleaning and Pest Control Workers	0.13
Cattle industry	0.11	Helpers, Construction Trades	0.11
Textile Product Mills	0.11	Other Food Preparation and Serving	0.11
Wood Product Manufacturing	0.10	Other Production Occupations	0.11
Administrative and Support Services	0.10	Material Moving Workers	0.11
Nonmetallic Mineral Product Manufacturing	0.09	Assemblers and Fabricators	0.10
Merchant Wholesalers, Nondurable Goods	0.09	Woodworkers	0.09
Waste Management and Remediation Services	0.09	Supervisors, Building and Grounds Cleaning	0.08
Food Services and Drinking Places	0.08	Metal Workers and Plastic Workers	0.08
Warehousing and Storage	0.08	Construction Trades Workers	0.08
Accommodation	0.08	Supervisors, Food Preparation and Serving	0.07
Repair and Maintenance	0.08	Forest, Conservation, and Logging Workers	0.06
Plastics and Rubber Products Manufacturing	0.07	Vehicle and Mobile Equipment Mechanics	0.06
Textile Mills	0.07	Supervisors, Production Workers	0.06

Top-20 industries (left) top-20 and occupations (right) of Mexican workers in the U.S.. The two lists are ordered by the share of Mexican workers (i.e., L_k^{MX}/L_k, with k indexing either an industry or an occupation). The overall share of Mexican employment in the US economy in 2005 is about 4%. Consequently, the listed activities represent actiivties in which Mexican workers are overrepresented. The industry column uses 3-digit NAICS industry classes, while the occupation column uses 3-digit SOC occupation classes.

Table 2: Age and education (IPUMS and ENOE, 2005)

	Non-Mexicans in US	Mexicans in US	Mexicans in Mexico	Returnees in Mexico
Average Age	41.22	36.66	37.09	33.27
Average Years of Schooling	13.43	10.00	8.31	7.41

Source: IPUMS for U.S. (first two columns) and ENOE for Mexico (last two columns) .

Columns (1) through (3) of Table 3 show the result of an Ordinary Least Squares (OLS) regression of $LQ_{is}^{mig,US}$ on $LQ_{is}^{loc,US}$ and $\sum_{s'} \frac{M_{s's}}{M_s} LQ_{is'}^{MEX}$. The latter term represents the weighted average location quotient of industry i in Mexican states, using the estimated migration flows, $M_{s's}$ from the Mexican state s' to the US state s as weights. This variable captures the expected prior work experience profile of Mexican immigrants in the US state. Columns (4) through (6) show the results of an analogous regression for the occupational choices of Mexican workers in the U.S..

The local supply of jobs is an important predictor for the type of work that Mexicans perform in the U.S.. In contrast, there is no evidence that Mexican immigrants select those US destinations

Table 3: Similarity in specialization (2005)

	k=industry			k=occupation		
	(1)	(2)	(2)	(4)	(5)	(6)
$LQ_{ks}^{loc,US}$	0.42***		0.41***	0.74***		0.74***
	(0.05)		(0.05)	(0.08)		(0.08)
$\sum_{s'} \frac{M_{s's}}{M_s} LQ_{ks'}^{MEX}$		0.09	0.05		-0.16	-0.28
		(0.11)	(0.11)		(0.21)	(0.21)
R^2	0.02	-0.00	0.02	0.03	-0.00	0.03
N	3239	3239	3239	3251	3251	3251

The dependent variable is $LQ_{ks}^{mig,US}$, the specialization of Mexicans in the U.S.. This is regressed against the specialization of non-Mexican in the U.S. (first row) and the specialization of Mexicans in their state of origin (second row). For columns 1–3 k, indexes industries, while for columns 1–4, k indexes occupations.

in which the demand for their skills is highest. This suggests that Mexican workers first choose a destination within the U.S., possibly informed by their existing social networks in the U.S. (see, for instance, McKenzie and Rapoport, 2010). Once arrived, they then adapt to the work they can find in their destination. This will be important in our identification strategy, because it suggests that the US work experience of returnees is not correlated with the economic structure of their home state in Mexico.

Another important question is whether the typical stay in the U.S. is long enough for Mexican immigrants to acquire new skills. There is some reason to believe that this is the case. Based on the EMIF Norte survey, the median first-time Mexican immigrant is 21 years old. In contrast, based on data from the Mexican Population Census and ENOE, the median age of return migrants to Mexico is 31. The age span between these two data points suggests that migrants spend important formative years of their working life in the U.S.. Moreover, given that immigrants tend to adjust to the jobs that are available around them, working in the U.S. should allow them to acquire different skills from what they learned at home. It is therefore plausible that upon their return, these immigrants carry new know-how back to Mexico. This potentially gives rise to knowledge spillovers in the local economies to which they move back. In the empirical section, we explore whether there is some evidence of knowledge spillovers in how wages and employment in local industries respond to the arrival of returnees.

2 Modeling the dissipation of migration effects

Estimating the causal effects of immigration on local workers is complex. First of all, migration is rarely random: migrants often leave places with poor prospects for regions where they can build a more secure and prosperous existence. Any statistical analysis therefore requires a careful identification strategy. We will leave this concern for later and return to it in the empirical section. Second of all, the effects of migration may not be limited to the regions where migrants arrive. This insight evoked a critique of studies that aim to estimate the impact of immigrants on local workers by comparing locations that receive such immigrants to locations that don't.[6] In this approach, immigration is thought of as a "treatment." The challenge is to estimate the effect of this treatment on local workers by finding regions that experience an exogenous increase in immigration. Workers in regions that do not experience any increase in immigration now serve as "untreated" counterfactuals. However, migration scholars (e.g., Borjas et al., 1996) have pointed out that these counterfactuals may be improper, because local workers in treated regions may respond to the treatment by relocating to untreated regions. This effectively washes out the treatment effect across the national economy. Consequently, a comparison between regions with and without immigration will fail to reveal the full impact (positive or negative) that immigrants exert on local workers.

We contend that such migration effects can still be uncovered by examining the timing of effects and the interplay of wage and employment dynamics. The Mexican returnees that are the focus of our study may indeed cause local workers to relocate to cope with the (positive or negative) shock returnees cause in local labor markets. This internal labor mobility may undo or, at least, narrow, any wage differentials in the wake of the returnees arrival. However, before this can happen, some wage differences must arise that relocating workers can exploit. In other words, for long-run effects of return migration to dissipate through labor reallocation within the wider Mexican economy, some differences in wages must appear in the short run. Moreover, the reallocation of workers itself will leave a measurable imprint on the employment distribution across cities and sectors. As we will argue below, there is little reason to expect long-term equalization of employment across Mexican labor markets. Therefore, unlike changes in wages, changes in employment levels are likely to be permanent. This suggests that we can assess the effects of Mexican return migration from the U.S. in two ways: first, by studying the *temporal* pattern of wage changes and, second, by studying the (permanent) changes in employment levels across localities in Mexico.

We will illustrate this reasoning with a highly stylized model that allows us to think through the adjustment processes that a migration shock sets in motion. The backbone of our analysis is a canonical two-by-two-by-two model. We consider three dimensions along which labor can be reallocated: cities, industries and occupations. That is, workers can respond to a migration-induced decline in wages by seeking new employment opportunities in less affected cities, industries or occupations. Which of these adjustment channels dominates will depend on the relative costs of changing jobs across space, industries or occupations.

Model setup

Let us assume a simple Cobb-Douglas, constant return to scale (CRS) economy with two cities ($c = \{1, 2\}$), two industries ($i = \{A, B\}$)) and two occupations ($o = \{\phi, \omega\}$). The only factors of production are workers, who are skilled in either occupation. This leads to the following production function:

$$y_{ci} = P_i \theta_{ci} L_{ci\phi}^{\alpha_i} L_{ci\omega}^{1-\alpha_i}, \tag{1}$$

where y_{ci} is output measured in value, P_i the price of the good produced by industry i, θ_{ci} the total factor productivity (TFP) in city c's industry i and L_{cio}, the supply of workers in city c employed by industry i skilled in tasks associated with occupation o. The exponents in (1) are such that industry A is relatively intensive in occupation ϕ: $\alpha_A > \alpha_B$. Furthermore, we will assume that trade with the rest of the world is frictionless, such that the same good has identical (exogenous) prices in all cities.

[6] A prime example of this approach is the work by Card on Cuban immigration to Miami during the Mariel boatlift (Card, 1990).

For expositional clarity, we do not allow cities here to have different productivities.[7] That is, we set $\theta_{ci} = \theta_i \ \forall c$, regarding return migration, m_{cio}, exclusively as an increase in the supply of workers in city c with experience in industry i and occupation o:

$$m_{cio} \equiv \Delta L_{cio} \tag{2}$$

As a result, the short-run impact of return migration on wages is determined by the labor demand of firms, which can be derived from the first-order conditions of firms' profit maximization problem. For instance, for workers skilled in occupation ϕ, we have:

$$w_{ci\phi} = P_i \theta_i L_{ci\phi}^{\alpha_i - 1} L_{ci\omega}^{1-\alpha_i} \alpha_i, \tag{3}$$

A supply shock ($\Delta L_{ci\phi}$) will thus have a negative short-run effect on wages.

Below, we study what happens in the longer run, when the labor market adjusts to the arrival of the returnees. The long-run equilibrium is pinned down by allowing worker mobility to clear labor markets across one of three dimensions: cities, industries, or occupations. We will work through three scenario's, in each of which we allow for only one adjustment channel to operate at a time. This corresponds to a situation in which labor moves along this dimension much more rapidly than along the other dimensions. For instance in the first model we assume that workers move more easily between cities than between jobs in different industries or in different occupations. This assumption is reasonable if skills are highly specific to an industry or an occupation and job switches involve lengthy reskilling trajectories.[8]

Scenario 1: mobility across cities

When it is easiest for workers to move between cities, wage differences will dissipate geographically, but not between industries or occupations. The equilibrium conditions in tis case are

$$w_{(c=1)io} = w_{(c=2)io} \quad \forall i, o \tag{4}$$

From equation (3), we obtain the following occupational wage-ratio for each city-industry combination

$$\frac{w_{ci\phi}}{w_{ci\omega}} = \frac{\alpha_i}{1-\alpha_i} \frac{L_{ci\omega}}{L_{ci\phi}}. \tag{5}$$

Because equation (4) implies that, in the long run, these wage ratios have to be identical across cities, we get that also employment ratios need to become equal

$$\frac{L_{1i\omega}}{L_{1i\phi}} = \frac{L_{2i\omega}}{L_{2i\phi}} \tag{6}$$

If immigration creates an imbalance in these ratios, internal migration between Mexican cities will restore the spatial equilibrium. Note, however, that this rebalancing can occur in two ways. Workers who are specialized in occupation ϕ, in which industry i is intensive, may move *out of* the affected

[7] We come back to it section 4.3, where we discuss the implications of relaxing this assumption.

[8] The consensus in labor economics seems to be that human capital is occupation (Kambourov and Manovskii, 2009) – or, rather, task (Gathmann and Schönberg, 2010) – specific than industry specific. Similarly, some urban economists have argued that cities specialize more and more in functions (occupational groupings) rather than industries (e.g., Duranton and Puga, 2005). However, others also document industry-specific components in human capital (e.g., Sullivan, 2010).

city (city 1). Alternatively, workers who are specialized in ϕ's complement, occupation ω, could move *into* city 1. Most likely, both processes will happen simultaneously. It is therefore in principle unclear whether employment in the city-industry that receives returnees will grow or decline after the initial influx of returnees. However, if mobility rates in either direction are more or less equal, we would expect that the net flow is close to zero.

Furthermore, while, in the long run, wages must equalize across cities, they need not return to their original levels. In fact, one can see in (3) that the new equilibrium employment ratio will permanently lower wages in receiving industry-occupation cells (and increase wages in the complementary occupations in the receiving industry) in both cities.

Scenario 2: mobility across industries

When workers are, instead, mobile across industries but not cities or occupations, the following set of long-run equilibrium conditions holds:

$$w_{c(i=A)o} = w_{c(i=B)o} \quad \forall c, o \tag{7}$$

Under this scenario, labor is not industry specific. Therefore, different industries in a city must pay the same wages to workers in the same occupations. This scenario is comparable to a Heckscher-Ohlin world, except for prices of final goods being fixed.

Unlike what happened in scenario 1, where employment ratios (and therefore wages) were forced to adjust, the entire shock can be absorbed by workers changing industries within a city. As a result, the specialization of city 1 will change, while keeping occupational employment ratios (and wage levels) constant. This standard result, known as factor price insensitivity, essentially states that, as long as the change in factor endowments stays within the cone of diversification (Leamer, 1995), changes in factor endowments will only affect the relative specialization between industries, but have no effect on factor prices.

The output change required to accommodate this shock is such that the industry that uses the more abundant factor intensively expands more than proportionally. These Rybczynski effects can be written in the notation of our model as[9]

$$\frac{\partial L_{ci}}{\partial L_{c\phi}} = \frac{w_{c\phi}/w_{c\omega} + (\alpha_A)/(1-\alpha_A)}{(\alpha_A)/(1-\alpha_A) - (\alpha_B)/(1-\alpha_B)}. \tag{8}$$

Note that $\partial L_{ci}/\partial L_{c\phi}$ is always positive by virtue of the assumption that $\alpha_A > \alpha_B$.

Finally, it is worth highlighting that – with factor prices pinned down by prices of a traded good – the two cities will have identical wages (before and after the shock), even if the equilibrium conditions (7) of this scenario do not require this to be the case.

Scenario 3: mobility across occupations

In the third scenario, workers can move across occupations, but not between cities or industries. This gives rise to the following equilibrium conditions:

$$w_{ci(o=\phi)} = w_{ci(o=\omega)} \quad \forall c, i \tag{9}$$

[9] To see this: (a) combine first-order conditions with resource constraints $L_{cA\o} + L_{cB\o} = L_{co}$ to obtain the equilibrium L_{cio} as a function of the wage ratio, α_A, α_B, $L_{c\phi}$, and $L_{c\omega}$; (b) express L_{ci} as $L_{ci\phi} + L_{ci\omega}$; (c) differentiate this expression with respect to $L_{c\phi}$.

Perfect mobility across occupations means that workers in different occupations (but in the same city-industries) are indistinguishable in the long-run. We can therefore rewrite the first-order and zero-profit conditions as

$$P_i = \frac{w_{ci}}{\theta_i} \tag{10}$$

With workers trapped in a city-industry cell, this describes a scenario in which no long-run adjustment takes place. Wages will stay constant as indicated in equation (10) and city-industry employment will only initially expand to absorb the returnees, but would subsequently have reason nor opportunity to adjust.

Summary of expectations

The scenarios sketched above suggest that whether short-term effects of return migration dissipate is related to how workers move within the Mexican economy. Depending on whether workers are predominantly mobile across cities, industries or occupations, we expect different temporal patterns for migration effects. We summarize these expectations in Table 4.

Table 4 provides a road map for analyzing the impact of return migration on local workers in Mexico.

A first discriminant for assessing how Mexican labor markets adjust to the influx of returnees from the U.S. is employment. If workers exclusively move across occupations or between cities, city-industry employment is most likely to remain unchanged (although, as discussed some uncertainty in this case exists). In contrast, if workers can switch jobs between industries, city-industry employment will expand beyond the initial influx of returnees until the wage imbalances caused by immigration are undone.

A second discriminant is wages. While in the short run the wage in a city-industry cell is expected to decline for workers who are employed in the same occupations as the returnees in any of the mobility scenarios, in the long-run important differences arise. If workers are mobile across industries or occupations, wages will equalize across all margins. If workers are only mobile across cites, wages only equalize between, not necessarily within, cities. That is, the ratio $w_{cio}/w_{c'io}$ will be unaffected by return migration, while all other wage ratios will exhibit a permanent negative effect.

Similarly, one can also look at the impact on wages in the affected city-industry, but in other occupations. This is an alternative way to look at complementarities. The expectations are, in this case, inverted, compare to those on wages of the own occupations, with a positive impact of migration in all cases in the short run, fading away at some margins in the long run.

The short- and long-run employment and wage responses to return migration summarized in Table 4 should be sufficient to identify how local labor markets react to migration shocks. However, if return migrants do not just expand the local labor supply but also bring with them new know-how, we may observe patterns that deviate from the ones reported in this table. In fact, the listed model variations will prove insufficient to account for all of our empirical findings. Therefore, later on in section 4.3, we will extend the model by allowing the Hicks-neutral technology shifter to vary across cities and to respond to return migration.

Table 4: Expectations on impact of m_{cio}, for different adjustment channels

	margin	dummies	S1: city mobility s.r.	S1: city mobility l.r	S2: ind mobility s.r.	S2: ind mobility l.r	S3: occ mobility s.r.	S3: occ mobility l.r
impact on employment								
	L_{ci}		=/?	=/?	+	+	=	=
comparing cities	$L_{ci}/L_{c'i}$	ρ_i	=/?	=/?	+	+	=	=
comparing industries	$L_{ci}/L_{ci'}$	ρ_c	=/?	=/?	+	+	=	=
comparing ratios	$(L_{ci}/L_{ci'})/(L_{c'i}/L_{c'i'})$	ρ_c,ρ_i	=/?	=/?	+	+	=	=
on wages								
	w_{cio}		-	-	-	=	-	=
comparing cities	$w_{cio}/w_{c'io}$	ρ_{io}	-	=	-	=	-	=
comparing industries	$w_{cio}/w_{ci'o}$	ρ_{co}	-	-	-	=	-	=
comparing occupations	$w_{cio}/w_{cio'}$	ρ_{ci}	-	-	-	=	-	=
on wages of other occupations								
	$w_{cio'}$		+	+	+	=	+	=
comparing cities	$w_{cio'}/w_{c'io'}$	ρ_{io}	+	=	+	=	+	=
comparing industries	$w_{cio'}/w_{ci'o'}$	ρ_{co}	+	+	+	=	+	=
comparing occupations	$w_{cio'}/w_{cio''}$	ρ_{ci}	+	+	+	=	+	=

The first four rows refer to the effect of wages of non-migrants in the same industry-city-occupation. The last four rows refer to the effect of employment in the city-industry. The column 'dummies' indicates which dummies are required to estimate the effect indicated in the column 'margin' (see discussion in section 3). The symbols +, -, and = indicate, respectively, a positive, negative, and zero expected outcome. For employment in the S1 scenario, we mark with =/? the fact that we expect on average no-change, although positive and negative outcome are possible. Short-run and long-run impact indicated by columns s.r. and l.r..

3 Empirical strategy

Regression set-up

Our model's predictions are framed in terms of wage and employment ratios across cities, industries and occupations. For instance, if workers can only change jobs geographically, we expect return migration in city-industry-occupation cell $(1, A, \phi)$ to have no long-run effects on wage ratio $\frac{w_{1A\phi}}{w_{2A\phi}}$. That is $\partial \frac{w^{t+T}_{1A\phi}/w^t_{1A\phi}}{w^{t+T}_{2A\phi}/w^t_{2A\phi}} / \partial m^t_{1A\phi} = f'(m^t_{1A\phi}) = 0$.

Using a multiplicative functional form suggests the following regression equations:

$$\log L^{t+T}_{ci} = \delta \log L^t_{ci} + \beta \log m^t_{ci} + \rho_i + \epsilon_{ci}, \tag{11}$$

and

$$\log w^{t+T}_{cio} = \delta \log w^t_{cio} + \gamma \log L^t_{cio} + \beta \log m^t_{cio} + \rho_{io} + \epsilon_{cio}, \tag{12}$$

where δ captures mean-reversion effects, γ potential urban scale effects (i.e., agglomeration externalities) and ρ_i and ρ_{io} represent an industry and occupation-industry fixed effects. These latter terms absorb the log-transformed numerator of the employment, respectively, wage ratios, e.g., $\log w_{c'io}^{t+T} - \log w_{c'io}^{t}$. Therefore, it allows us to interpret the coefficient of return migration, β, as the effect on the ratio of employment or wages between the focal city c and other cities in the sample for workers who occupy the same industry or industry-occupation cell (i, o). Similarly, we can test predictions on other ratios by adding adequately chosen dummy-groups to the regression equation (see third column of Table 4).

Data

Our main dataset is based on the ENOE (Encuesta Nacional de Ocupación y Empleo). The ENOE was established by the Mexican statistical office (INEGI) to keep track of employment dynamics. It collects individual-level information for a rotating sample of about 550,000 Mexicans in each year since 2005, with a focus on labor market outcomes. We will use the data available for the period 2005-2013. Among the available variables are an individual's industry, occupation and municipality of residence, as well as her monthly wage. Further details on the ENOE are provided in Appendix B.2.

We aggregate the ENOE to calculate employment and (L_{cio}^{t}) and wages (w_{cio}^{t}) at the level of city-industry-occupation cells. "Cities" refer here to functional spatial units, so-called *Zonas Metropolitanas*, henceforth *ZMs*), as defined by the statistical office. These spatial units roughly correspond to commuting zones. Because ZMs do not cover the entire surface of the country, we add to this the conglomerate of all municipalities in rural areas in a given state that do not belong to any ZM. This yields a total of 90 geographical units.[10] Industry and occupation classes are harmonized across years and between Mexico and the U.S.. As a result, we distinguish among 64 industries and 27 occupational classes. Details on this procedure are provided in Appendix C.3.

The ENOE also allows us to measure return migration by city-industry-occupation cell. To do so, we exploit the fact that the survey asks whether the participant had recently relocated from abroad. Unfortunately, the survey does not record from where the participant relocated. However, based on a 10% sample of the 2010 Mexican population census, we find that the provenance of 96% of returnees between 2005 and 2010 is the U.S.. Therefore, we will assume that all return migrants come from U.S..

Table 5 provides descriptive statistics for the main variables derived from the ENOE at the city-industry level for the years 2007 and 2013.[11] About 0.5% of the Mexican workforce consists of workers who have returned from a stay abroad over the course of the previous two years (2006 and 2007). These workers are relatively concentrated within a select number of city-industries: less than a quarter of city-industry observations has any exposure to return migration.

Instrumental Variable

So far, we have ignored the fact that return migration is not random. However, Mexicans in the U.S. are likely to base their decision whether or not to return to Mexico on the existing employment opportunities. In particular, workers will be more likely to return to a Mexican city the more likely

[10] In robustness checks, we also exclude such rural areas (see Table A.1). Further details about the regional definitions are provided in Appendix C.1.

[11] Note that employment need not be integer-valued, because the data are aggregated from quarterly data. Furthermore, combining 90 geographical units with 64 industries yields a total of 5,760 potential observations. Of these, we only include 4,131 observations for which employment is non-zero in both years. A similar number of non-zero observations is found in the wage data.

Table 5: Descriptive statistics at the city-industry level (source: ENOE)

Variable	Obs	Mean	Std. Dev.	Min	Max
Employment 2007	4,131	10757.27	44545.15	5	1775310
Employment 2013	4,131	11804.12	50337.06	8.25	2045924
Growth employment	4,131	1.603654	2.579786	0.008841	59.35353
Wages 2007	4,100	61947.37	38921.16	552	600000
Wages 2013	4,075	67824.63	40863.54	2064	653899.1
Growth wages	4,046	1.263726	0.997859	0.053826	23.25581
US returnees	4,131	53.86662	348.6915	0	9296.25

Wages are measured in current Pesos and they refer to the yearly labor remuneration.

Table 6: Distribution of length of stay in the U.S. before apprehension (*Devueltos*)

Length of migration	Freq.	Percent
Less than a week	240	1.45
Less than a month	524	3.17
Less than a year	2,921	17.67
More than a year	13,606	82.33
Total	16,527	100

Sub-sample of deported migrants who declared to have worked in the U.S..

they believe it to be that they will find jobs that match their skills. Therefore, we expect to observe that city-industry-occupation cells with many return migrants will also display a high growth in wages and employment. However, it is unclear whether the higher wages are a consequence or a cause of return migration.

To assess the direction of causation, we will rely on instrumental variable (IV) estimation. We base our instrument on a dataset that surveys people crossing the US-Mexican border, the *Encuesta sobre Migración en la Frontera Norte de México*, henceforth, EMIF Norte.[12] The survey has collected yearly information on tens of thousands of migrants crossing the border in either direction since the late 1990s. Within EMIF Norte, we focus on the *Devueltos* survey. This survey contains interviews with a large sample (between 6,000 and 10,000 per year) of migrants that were forcibly returned to Mexico by US authorities. It mainly intends to document migrants apprehended in illegal border crossings. These migrants are sent back to Mexico immediately, often within hours and without trial. However, approximately one third of interviewees declared to have worked in the U.S. before their apprehension. The majority of this latter group had stayed in the U.S. for an extended period: about 80% of them had stayed for over a year and only about 3% for less than a month (see Table 6).

[12]This is the same dataset we used to produce the figures in section 1. Several institutional partners contribute to this survey, including the Consejo Nacional de Población (CONAPO). For a full list of participants see https://www.colef.mx/emif/instituciones.php

As shown in Figure 2, the group of deportees is large, representing the majority of return migrants. Unlike regular return migrants, deportees do not choose to leave the U.S. to seek employment opportunities in Mexico. As a consequence, their departure can be regarded to be exogenous to economic conditions in Mexico. However, which destination they choose within Mexico may still be endogenous. After all, deportees will still be attracted to growing places and industries, because they offer favorable employment opportunities. Consequently, even when limiting the analysis to deportees, there is still a risk of reverse causality.

To resolve this issue, we use the information on the number of deportees in an indirect way. First, we select all respondents in *Devueltos* who declared to have worked in the U.S.. Next, we extract information about the occupation and industry of the last known job the deportees had in the U.S., as well as, about their city of birth in Mexico. This information allows us to *predict* where deportees will go, assuming that they will return to their city of birth and work in the industry and occupation in which they had worked in the U.S.. Whereas the *actual* destination city, industry and occupation may be endogenous to existing employment opportunities, the *predicted* destination does not use any information that would be affected by current economic conditions in Mexico. We construct the IV year-by-year from 1999 onward, although for the benchmark analysis we take two years of deportation: 2006 and 2007 (the same two years we use from the endogenous variable from the ENOE).

4 Results

4.1 Impact on employment

Benchmark regression

Our model yields predictions for how two distinct variables will react to an influx of return migrants: the employment in a city-industry and the wages in city-industry-occupation cells. Under most scenarios, we expect that return migrants permanently raise employment levels in the city-industry in which they find employment. In contrast, wage effects will typicaly be temporary. With time, they dissipate across space, industries or occupations.

We start by analyzing employment dynamics. Table 7 shows the effects of return migrants on employment growth in city-industries across Mexico, when we use a 5-year time horizon. Note that we measure the growth of employment for *locals*, i.e., excluding the jobs taken by the returnees themselves. The different models in the table control for industry and/or city fixed effects.

The employment effects can dissipate across different mobility channels, each of which is associated with its own employment ratio and isolated with a specific set of fixed effects. For instance, column (2) contains industry fixed effects. It therefore effectively studies changes an industry's employment ratio between different cities (i.e., $\frac{L_{ci}}{L_{c'i}}$). If local economies respond to return-migration shocks through a redistribution of workers across cities, we expect that, holding the industry constant, effects of return migration quickly disappear. Given that we still have a surplus of workers in the industry that received returnees, albeit now spread out across cities, we could still observe return migration effects when comparing different industries in the same city (as in column (3)).

Table 7 suggests that return migration shocks raise a city-industry cell's long-run employment levels, regardless of whether we compare across industries in the same city or across cities for the same industry. In fact, also when we compare the industry employment ratios across cities, we observe a permanent effect of return migration. Interpreted through our earlier model predictions, this means that workers would need to be able to move across industries – inducing Rybczynski effects – or cities,

Table 7: OLS regressions - impact of return migration on long-term employment

OLS - Dependent variable: 5-year employment growth				
	(1)	(2)	(3)	(4)
US returnees	0.016***	0.016***	0.018***	0.015***
	(0.003)	(0.003)	(0.002)	(0.003)
Employment level	-0.108***	-0.177***	-0.126***	-0.32***
	(0.011)	(0.022)	(0.011)	(0.021)
Constant	0.983***	1.467***	1.408***	1.365***
	(0.097)	(0.242)	(0.096)	(0.333)
Industry dummies	N	Y	N	Y
City dummies	N	N	Y	Y
Observations	4131	4131	4131	4131
R-Squared	0.05	0.15	0.11	0.27

*City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively. All variables in logarithm*

or both. Occupational mobility alone would be insufficient to explain these effects.

While the OLS regressions reveal a positive association between return migration and employment, the question is whether these associations reflect causal mechanisms. To assess this, Table 8 reports the outcomes of Two-Stage Least Squares (2SLS) models that use our predicted involuntary return migration flows as an instrument.

The first-stage F-tests report heteroscedasticity-robust Kleibergen-Paap statistics. Across all specifications, this statistic indicates that the instrument is reasonably strong:[13] the predicted migration rates based on deportees' place of birth and former US industry affiliation are a sufficiently strong predictor of the observed return migration flows into a city-industry in Mexico.

The estimated elasticity of employment growth with respect to return migration lies between 6% and 10%. This suggests that a 10% increase in the number of return migrants in a city-industry cell leads to an increase in employment for local workers in that cell of between 0.6% and 1%. Note that these elasticities are higher than in our earlier OLS estimates. Apparently, the OLS models *under*estimate the true effects of return migration. On the one hand, this may simply reflect the reduction in efficiency of the 2SLS estimates compared to the OLS estimates, with standard errors increasing between 5 and 15-fold. On the other hand, it is unlikely that we will have measured return migration with perfect accuracy, given that the ENOE represents only a 0.4% sample of the Mexican labor force and that the timing and industry affiliation of return migrants will also be imperfectly captured.[14]

[13] In most specifications, the Kleibergen-Paap statistic stays well above the commonly used threshold of 10. Only when including both industry and city fixed effects does the statistic get close to this threshold. However, in this specification, the estimated 2SLS effects are actually relatively low, not high, as one would would have expected in the case of weak-instruments related biases.

[14] Such measurement errors would also explain why the mean reversion effect strengthens in the 2SLS models: because the underlying variable is positively correlated with the number of returnees, the mismeasurement of return migration

Table 8: 2SLS regressions - impact of return migration on long-term employment

2SLS, FIRST STAGE - Dependent variable: US returnees				
	(1)	(2)	(3)	(4)
Forced migration	0.27***	0.171***	0.242***	0.128***
	(0.027)	(0.034)	(0.028)	(0.032)
F-test	97.7	25.4	76.1	16.2
SECOND STAGE - Dependent variable: 5-year employment growth				
	(1)	(2)	(3)	(4)
US returnees	0.074***	0.097***	0.087***	0.072**
	(0.014)	(0.024)	(0.017)	(0.028)
Employment level	-0.171***	-0.251***	-0.209***	-0.372***
	(0.021)	(0.033)	(0.026)	(0.034)
Constant	1.728***	2.676***	2.013***	4.01***
	(0.221)	(0.33)	(0.229)	(0.283)
Industry dummies	N	Y	N	Y
City dummies	N	N	Y	Y
Observations	4131	4131	4131	4131

*City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively. All variables in logarithm*

To gain an understanding of how local economies adjust to an influx of returnees, Figure 4 shows how returnees affect employment of locals over different time horizons. Each panel corresponds to models that include different fixed effects, each of which corresponds to a different mobility channel. The faster estimated effects fade out in the presence of a certain type of fixed effect, the faster the associated channel re-equilibrates a local economy.

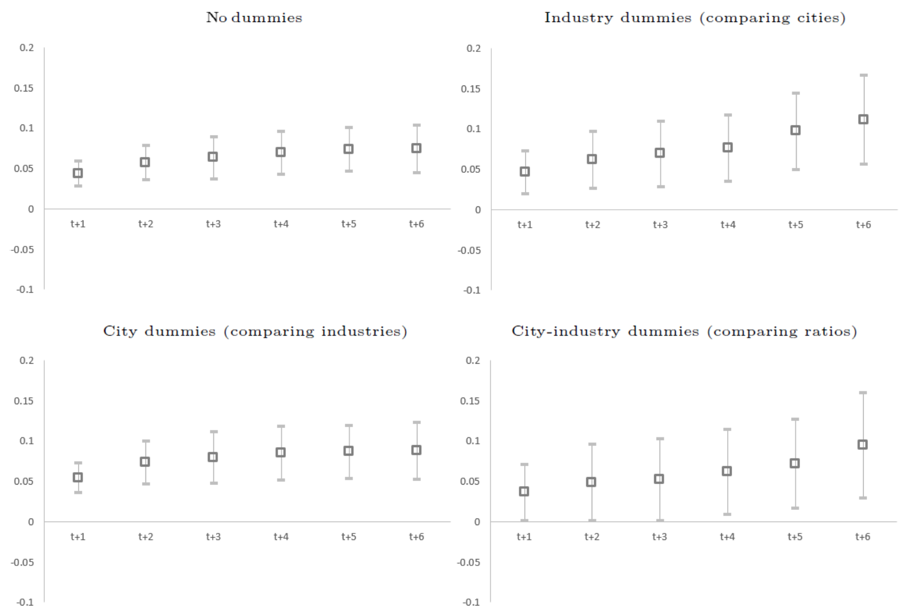
The temporal patterns are strikingly robust across the different models. They suggest that local economies slowly adjust to an influx of return migrants, steadily expanding employment for locals in the city-industry cells in which the returnees arrive. A more definitive conclusion on which channels are most important for moving local economies back to equilibrium will have to wait until we have analyzed local wages. However, before getting there, we will first assess the robustness of our findings so far.

Robustness of employment-growth regressions

To assess the robustness of our findings, we run several variations of the model specification and sample definitions. Results of this exercise are collected in Table A.1 of the appendix. First we exclude rural areas (i.e., the areas in Mexico that do not belong to a city – *zona metropolitana* – as defined by

would have lead to an overestimation of the mean reversion effect. That is, the mean reversion coefficient would not be sufficiently negative in the OLS estimates.

Figure 4: Employment elasticity plot



The horizontal axis indicates the length of the period considered (every corresponding estimate is computed between 2007 and 2007+T). The vertical axis indicates the elasticity of wages to return migrants in the city-industry. 95% confidence intervals (with city-level cluster robust standard errors) are marked by the vertical bars.

INEGI) and border states to eliminate any confounding effects of cross-border commuting. Second, we change how we quantify return migration, using different ways to deal with the fact that for many city-industry cells return migration flows are zero. Since our models are log-transformed, such observations would have to be dropped from the analysis. Instead, we substitute all zeros with a small number (ϵ=0.001) and show in two ways that the choice of ϵ is not decisive. First, we rerun the regressions with a different epsilon, 100 times smaller (ϵ = 1e-5) and 1,000 times larger ($\epsilon = 1$). Additionally, we go around the problem of log transforming a variable with observations with zero values, by running a regression where the dependent variable is log-transformed, but the independent variable is kept in levels. We also dichotomize the return migration variable, setting observations for city-industries to one if they receive returnees, and to zero if they receive no returnees at all. As a final check on the specification, we we alternatively measure return migration as a share of the city-industry's workforce. Across these models and sample definitions, we find positive effects of return migration and fairly similar point estimates, whenever these point estimates can be directly compared to the one's in the baseline models presented above.

Table 9: IV regressions robustness - control for pre-trend

2SLS, FIRST STAGE - Dependent variable: US returnees				
	(1)	(2)	(3)	(4)
Forced migration	0.27***	0.171***	0.242***	0.128***
	(0.027)	(0.034)	(0.028)	(0.032)
F-test	97.6	25.4	76	16.2

SECOND STAGE - Dependent variable: 5-year employment growth				
	(1)	(2)	(3)	(4)
US returnees	0.074***	0.097***	0.086***	0.072**
	(0.014)	(0.024)	(0.017)	(0.028)
Employment level	-0.17***	-0.25***	-0.208***	-0.372***
	(0.021)	(0.033)	(0.026)	(0.035)
Pre-trend	-0.008	-0.009	-0.008	-0.007
	(0.007)	(0.006)	(0.007)	(0.006)
Industry dummies	N	Y	N	Y
City dummies	N	N	Y	Y
Observations	4131	4131	4131	4131

*City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

Plausibility of the exclusion restriction

There are several potential concerns regarding our identification strategy. The first and, probably most important, concern is that persistence of economic conditions in Mexico may result in spurious correlations between the number of deportees that return to a city-industry and this city-industry's growth potential. For instance, if a city-industry has a persistently weak performance, it may have driven many local workers to emigrate to the U.S. in the past. In the U.S., this would have resulted in a sizable stock of migrants who originated from such city-industries. Such a large stock of migrants could later translate into a large number of deportees from these origins. If adverse conditions were to persist, return migration flows would correlate with contemporaneous economic conditions, even though they did not cause them. Note that this concern would explain why we *underestimate* the causal effects of return migration: a large inflow of returnees would correlate with a weak performance of the local economy, driving down the estimated effect of returnees on growth.

To check whether this narrative finds some support in our data, we include a variable that captures a city-industry's employment-growth pre-trend. We compute this pre-trend as the growth in employment between 2005 and 2006 (i.e., between $t_0 - 2$ and $t_0 - 1$). However, including such a pre-trend variable does not alter any of our results. In fact, as shown in Table 9, point estimates change by at most 1%, if they change at all.

To further assess whether persistence in return migration rates may be cause for concern, we explore what happens if we change the timing of our variable definitions. In particular, we ask whether return migrants affect growth in the period *before* they arrived. In particular, we measure the number of

Table 10: IV regressions robustness - timing of events

	[return years: 2006-2007]	[return years: 2012-2013]
2SLS, FIRST STAGE	depvar: US ret	depvar: US ret
	(1)	(2)
Forced migration	0.128***	0.078***
	(0.032)	(0.022)
F-test	16.2	12.8
SECOND STAGE	$\Delta E_{2007-2012}$	$\Delta E_{2007-2012}$
US returnees	0.072**	0.026
	(0.028)	(0.034)
Employment	-0.372***	-0.321***
	(0.034)	(0.028)
Industry dummies	Y	Y
City dummies	Y	Y
Observations	4131	4131

*City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

returnees in the years 2012 and 2013 and estimate their effect on growth in the 5-year period before their arrival. Note, however, that we do not change the instrument. The idea behind this is that we want to test whether any of the exogenous variation that our instrument detects in return migration after the window in which we measure growth predicts growth rates within this window. If it does, we would be concerned that the reduced-form effect of our instrument on employment growth does not run through the return migration variable itself, but through some other channel that is persistent over time.

The results of this exercise are shown in column (2) of Table 10, next to the benchmark estimate, which is reported for convenience in column (1) . Note that the first-stage regression remains highly significant. This means that predicted returns today correlate with actual return migration in prior years. However, the second-stage results have turned insignificant: reassuringly, the exogenous variation in returnees does not correlate with employment growth in prior years.

A final concern is that we may have neglected some pull factors that correlate in non-obvious ways with deportation rates by city-industry. For instance, immigrants in the U.S. may be less careful to avoid deportation if they are less worried about their employment opportunities in their home town. In such a scenario, our effect estimates would be biased upward.

To gauge the plausibility of such potential pull factors biasing our results, we study internal migration flows between regions inside Mexico. The idea behind this is that if pull factors exist that somehow influence deportation rates, these same pull factors should also attract internal migrants from other cities within Mexico. Therefore, we would expect to see a correlation between the number of deportees and the number of internal migrants that a city-industry attracts.

We explore this hypothesis in Table 11. In column (1), we replicate the strictest model of our

Table 11: IV regressions robustness - Placebo test

	[standard]		[placebo]	
2SLS, FIRST STAGE	depvar: US ret		depvar: MX migr	
	(1)	(2)	(3)	(4)
Forced migration	0.128***	0.129***	-0.024	-0.033
	(0.032)	(0.032)	(0.027)	(0.027)
F-test	16.2	16.4	0.8	1.5
SECOND STAGE - Dependent variable: 5-year employment growth				
US returnees	0.072**	0.072**		0.051
	(0.028)	(0.028)		(0.055)
MX immigration		0.012***	-1.513	-0.442
		(0.003)	(5.909)	(0.658)
Employment level	-0.372***	-0.389***	1.664	0.222
	(0.034)	(0.033)	(7.679)	(0.801)
Industry dummies	Y	Y	Y	Y
City dummies	Y	Y	Y	Y
Observations	4131	4131	4131	4131

*City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

earlier analysis, which corrects for both industry and city fixed effects. Next, in column (2), we include a variable that captures the number of workers from outside the (Mexican) state who move into a city-industry. In as far as this variable captures pull factors that correlate with deportation rates, we would expect the 2SLS effect of return migration to fall. However, the point estimates in this model are exactly the same as those in column (1). In columns (3) and (4), instead of controlling for internal migration, we use the internal-migration variable in a placebo test. That is, instead of using predicted (forced) return migration as an instrument for actual (overall) return migration from the U.S., we use it as an instrument for *internal* migration within Mexico. The first-stage of this regression directly asks whether internal migration flows are (positively) correlated with our deportation-based instrument. The answer is no: the effect of the instrument on internal migration flows is negative and insignificant. As a result, the second stage effects of internal migration on employment growth are insignificant as well. Taken together, these results corroborate the validity of our identification strategy.

Alternative dataset

As a final check, we assess whether results change when we rely on completely different data to measure return migration and city-industry employment growth. To do so, we estimate the impact of returnees on employment growth, using data from the economic census for the years 2004 and 2009 (which refer to economic activities in 2003 and 2008). The endogenous variable – returnees from the U.S. – is derived from the Mexican population census in 2000. As a consequence, return migration rates

Table 12: IV regressions robustness - Economic Census data

2SLS, FIRST STAGE - Dependent variable: US returnees				
	(1)	(2)	(3)	(4)
Forced migration (1999/2000)	0.295***	0.176***	0.227***	0.06***
	(0.017)	(0.016)	(0.016)	(0.014)
F-test	213.9	55.9	214.2	16.9
SECOND STAGE - Dependent variable: Employment growth (2003-2008)				
	(1)	(2)	(3)	(4)
US returnees (2000)	0.065***	0.049***	0.08***	-0.0001
	(0.009)	(0.017)	(0.012)	(0.053)
Employment level (2003)	-0.119***	-0.15***	-0.134***	-0.189***
	(0.012)	(0.018)	(0.015)	(0.031)
Constant	1.194***	1.288***	1.455***	0.284
	(0.102)	(0.194)	(0.131)	(0.543)
Industry dummies	N	Y	N	Y
City dummies	N	N	Y	Y
Observations	4447	4447	4447	4447

*City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

are measured four years before the base year of the employment growth variable. To calculate our instrument, we pool data for the years 1999 and 2000 from EMIF Norte Devueltos. Results are shown in Table 12.

Overall, outcomes point in the same direction as before. Effects of return migration are positive and centered on around the same elasticity as in the ENOE-based analyses. However, when using economic census data, the range of point estimates is wider. For instance, the specification that controls for city and industry fixed effects even yields point estimates that are not statistically different from zero. However, taking into account that we could not perfectly align the timing of return migration with the base year of the growth variable, the results in Table 12 still provide a remarkably close corroboration of our earlier results.

4.2 Impact on wages

So far, we have documented that an influx of return migrants from the U.S. causes an expansion of the number of jobs for local workers in the city-industry cells of the returnees. The models in section 2 suggest that the most plausible explanation for this is that locals restore the local labor market equilibrium predominantly by moving between industries. The mechanism at work here is the Rybczynski effect: the wage drop in affected occupations in the returnees' city-industry cells is compensated by a wage increase in unaffected occupations. This leads to an influx of workers in the latter occupations from outside the city-industry cell that exceeds the outflow of workers in the affected occupation. In the long run, wage effects disappear, but employment effects persist.

A second possibility is that workers respond to the initial wage drop in the affected city-industry cell by relocating to other cities. However, on the face of it, in this case we would expect the city-industry to have shrunk.[15]

A third, so far neglected, possibility is that returnees do not just raise the local supply of labor, but also carry with them valuable knowledge that allows local industries to outcompete industries elsewhere in Mexico. In this case, local employers' elevated productivity would allow them to pay higher wages. Wages would then not need to have dropped, but could actually have risen in the city-industries where returnees appeared. Therefore, in this section, we look more carefully into the wage dynamics that return migrants from the U.S. set in motion.

How local wages will respond to immigration depends on the relation between locals and immigrants (e.g., Ottaviano and Peri, 2012). If locals and immigrants are substitutes, immigration will put a downward pressure on the wages of local workers. In contrast, if immigrants complement the skills of locals, local wages may rise. Such positive wage effects may be further compounded by knowledge spillovers (as Moretti 2004 highlights, when modeling the social impact of education).

How do we know who will be affected positively and who will be affected negatively by the arrival of returnees? This depends on two aspects of the observed return migration. First, are the skills of local workers similar or different from the skills of returnees? If they are similar, locals should experience negative substitution effects. If they are different, locals may experience positive complementarity effects. Second, do local workers benefit from new know-how that returnees bring with them? We contend that this will depend on whether or not local workers are employed in the same productive units as the returnees. The idea behind this is that returnees may carry knowledge of advanced production processes and organizational routines that make local firms more productive.

Unfortunately, we do not observe firms in our data. Therefore, we will think of city-industry cells as proxies for productive units. In the models of section 2 – and assuming that knowledge spillovers are (at least in part) Hicks neutral[16] – this would mean that returnees change the technology parameter θ_{ci}. Consequently, returnees will boost the productivity – and thus pay – of all workers in a local industry. For locals with similar skills as the returnees, this spillover effect would dampen or even overturn the negative substitution effect. Other workers, in contrast, get these benefits without the costs of immigration. They would only experience the positive spillover effects and would therefore see their wage increase. Over time, the productivity effect will fade when knowledge diffuses within Mexico. At that point, also wage effects would disappear.

In contrast to knowledge spillovers, substitution and complementarity effects are less concentrated within the local economy. The reason is that these effects emerge, because returnees change the local supply of labor. This shift in the relative supply of local skills should be felt throughout the local economy, not within a single industry.[17]

As common in the migration literature (for an overview of the typical approaches see Dustmann et al., 2016), we will proxy the skills of returnees by the broad occupation in which they had worked before. The idea behind this is that workers in the same broad occupational class will carry out similar tasks. Therefore, if return migrants are experienced in the same occupation as a local worker, this

[15] Although we believe this is the most plausible outcome, strictly speaking, the net worker flow between the affected and other cities may be positive. Towards the end of this section, we will discuss this possibility in more detail.

[16] Note that returnees could theoretically also carry skill-specific knowledge. In this case, knowledge spillovers will mostly affect locals with similar skills. However, due to simultaneous substitution effects, the consequences of return migration would be ambiguous. We further note that, if we strictly adhere to the Cobb-Douglas framework presented in section 2, skill-specific knowledge spillovers have a Hicks neutral representation.

[17] Also see footnote 8.

Table 13: IV regressions on wages at the city-occupation level (3-year growth effects)

Dependent variable: 3-year growth in wages for non-migrants								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage in occupation	-0.689***	-0.707***	-0.751***	-0.766***	-0.68***	-0.703***	-0.752***	-0.769***
	(0.048)	(0.065)	(0.077)	(0.104)	(0.014)	(0.047)	(0.082)	(0.109)
Emp. in occupation	0.135***	0.145**	0.183**	0.205*	0.058***	0.077	0.172**	0.18
	(0.048)	(0.065)	(0.077)	(0.104)	(0.014)	(0.047)	(0.082)	(0.109)
US migr. own occ.	-0.066*	-0.068**	-0.053**	-0.036***				
	(0.039)	(0.026)	(0.025)	(0.011)				
US migr. other occ.					0.002	0.28	-0.032	0.039
					(0.023)	(0.231)	(0.032)	(0.137)
F-test (first stage)	75.25	40.6	29.8	15.36	300.44	4.49	246.02	5.24
Dummies		c	o	c,o		c	o	c,o
Observations	1674	1674	1674	1674	1674	1674	1674	1674

*Cluster robust standard errors in parentheses (dummy dependent). Cross-section: industry-metropolitan area-occupation. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

local worker will be exposed to negative substitution effects. In contrast, the skills of local workers in different occupations are made relatively scarce by the returnees and may benefit from positive complementarity effects.

Note that, unlike the occupational dimension, existing migration studies typically neglect the industry dimension of migration.[18] As a consequence, these studies can only identify spillover effects that manifest themselves at the level of an entire city. However, at this level, spillover effects are much diluted. Instead, we will use the city-industry-occupation cell as a unit of analysis. This set-up isolates groups of workers that are most likely to experience knowledge spillovers from returnees and then splits these workers into subgroups with and without expected exposure to substitution and complementarity effects. By narrowing our focus on a specific industry within a city, we should increase the likelihood of identifying the various positive and negative effects from return migration. This heeds the advice of (Ottaviano and Peri, 2012), who stress the importance of distinguishing between worker groups that experience different consequences from being exposed to immigrants.

To explore these ideas, we first follow the bulk of the literature on migration and estimate the effect of return migration at the level of the city-skill-group cell, which we approximate by the city-occupation cell. Our instrument is constructed analogously to the instrument used in the employment regression. The only difference is that we now use the experience of deportees in terms of the *occupation* in which they had worked in the U.S.. Results are shown in Table 13.

The table summarizes the estimated effects of return migration on wage growth over a 3-year horizon.[19] It contains eight columns. The first four columns report effects of returnees in the same occupation as the locals, the last four columns of returnees in different occupations.[20]

[18]To be sure, some papers exist that identify the effect of immigration on workers in specific industries (i.e. Bahar and Rapoport, 2018). However, here, the occupational dimension is often missing to identify workers who may experience negative substitution effects.

[19]We test the impact on wages over a 1-, 2-, 3-, 4-, 5-, and 6-year horizon. In this section we only report the results for the horizon on which the estimated effect is strongest. For city-occupation cells, effects peak at 3 years. In other specifications, they peak at 2 years. Below, we will also graphically illustrate the wage dynamics at different time horizons. Tabular forms of these results are available upon request.

[20]Estimating these effects jointly in a 2SLS model with two endogenous variables is complicated by multicollinearity of return migration in different occupational groups. However, we report such a model with within and cross-occupational

Table 14: IV regressions on wages at the city-industry-occupation level (2-year growth effects)

Dependent variable: 2-year wage growth for non-migrants								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage in occupation	-0.849***	-0.9***	-0.904***	-0.899***	-0.845***	-0.898***	-0.904***	-0.894***
	(0.033)	(0.022)	(0.04)	(0.036)	(0.022)	(0.044)	(0.043)	(0.019)
Emp in occupation	0.214***	0.114***	0.328***	0.288***	0.174***	-0.008	0.325***	0.191***
	(0.033)	(0.022)	(0.04)	(0.036)	(0.022)	(0.044)	(0.043)	(0.019)
US migr in occupation	-0.111***	-0.031	-0.179**	-0.171***				
	(0.039)	(0.025)	(0.071)	(0.057)				
US migr in other occ.					0.016	0.197**	0.327**	0.051**
					(0.015)	(0.077)	(0.144)	(0.022)
F-test (first stage)	13.4	11.6	17.26	15.17	125.4	41.53	9.19	277.01
Dummies		i*o	c*i	c*o		i*o	c*i	c*o
Observations	12421	12314	11021	11984	11193	11089	11021	10776

*Cluster robust standard errors in parentheses (dummy dependent). Cross-section: industry-metropolitan area-occupation. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

The first-stage F-statistics do not raise any concerns about the instrument's strength. The only cases where the statistic is below 10 is when studying the effect of migration on the other occupation exploiting variation between occupations (columns 6 and 8).[21] As expected, the estimate works on a variation which is weak, and so is the first stage. In the second stage, we find significantly negative effects of returnees. However, these effects are only observed when returnees and locals work in the same occupations. This corroborates the hypothesis that returnees represent substitutes for local workers, but only if they have similar skills. However, note that we do not find any evidence that workers in other skill groups actually benefit from return migration. That is, in these models, we fail to identify any positive effects for locals for whom returnees represent complements.

Next, we rerun these regressions, but now at the level of the city-industry-occupation cell. The instrument here is based on information on the occupation and the industry in which deportees had worked in the U.S.. Results are shown in Table 14.

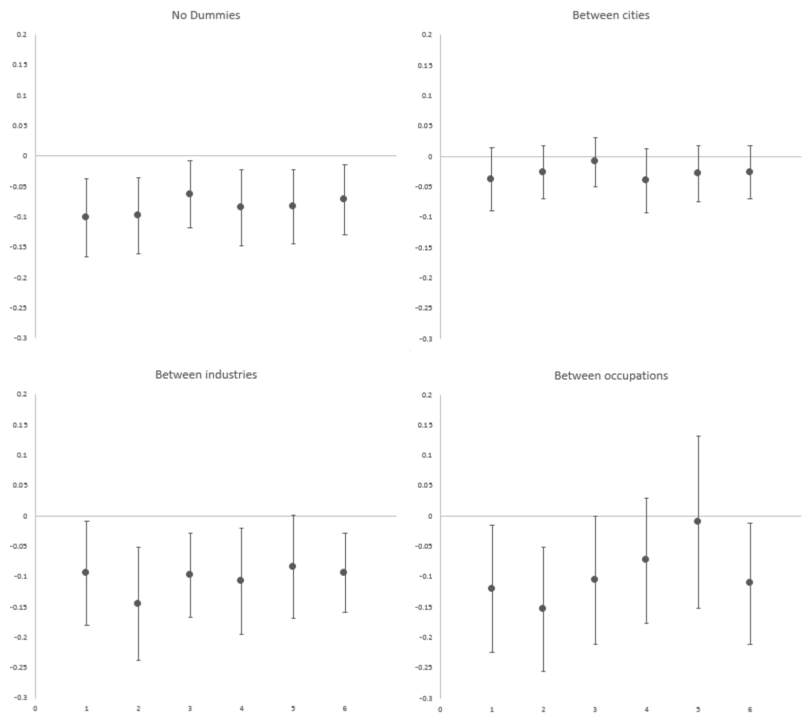
The table once again shows own-occupation and cross-occupation wage effects of return migration. As before, we find that returnees exert a significantly negative effect on locals' own-occupation wages. This effect is statistically significant in most specifications, with the exception of column (2), where we use industry-occupation dummies to compare workers in the same industry-occupation cell across cities. Furthermore, note, that the wage elasticity with respect to the number of returnees is larger, though less precisely estimated, than in the city-occupation analysis of Table 13. This shows that focusing on city-industries helps isolate workers who are more affected by returnees. At the same time, we now also find statistically significant positive cross-occupational effects in three of our four specifications.

To distinguish among different channels of adjustment, we need to determine how wage effects evolve over time. Figure 5 shows the dynamics of the negative own-occupational effects of return migration. The dynamics of positive cross-occupational effects are shown in the appendix in Figure A.1. These figures are based on models that are analogous to the ones in Table 14. They plot the

effects in the appendix (Tables A.3 and A.2). Results are similar to the ones presented here

[21]Note that this is the same for table 14, where the only F-statistic below 10 is in column 7, that is comparing occupations.

Figure 5: Dynamics of wages at the city-industry-occupation level. Effect on own occupation



Estimated impact of return migration at different time horizons. The horizontal axis represents T, the number of years over which growth is computed (between 2007 and 2007+T). The vertical axis the estimated elasticity of returnees. Vertical bars: 95% confidence interval

point estimates and 95% confidence intervals of return migration effects on wage growth at different time horizons. Each of the four graphs in Figure 5 (and the same goes for Figure A.1) shows this evolution of effect estimates in the presence of different dummy groups. Each dummy group interacts two dimensions, leaving open a third dimension across which individuals are compared. For instance, the models with occupation-industry fixed effects compare workers in the same occupation and industry but across different cities. Consequently, these regressions estimate the role of geographical mobility as the adjustment channel.

Without controlling for any dummies, we do not observe any positive cross-occupation effects, but we do observe negative own-occupation effects that slowly fade out. The fastest dissipation of these negative effects happens when we compare across cities, holding occupations and industries constant. When comparing workers across industries (or to a lesser extent, occupations) the negative own-occupation wage-effects of returnees diminish much more slowly and are still visible after six years. This suggests that there are high frictions that prevent mobility across these channels. Furthermore, in the regressions with fixed effects, we also tend to find positive cross-occupation wage effect. However, these seem to dissipate at a more or less equal rate across any of the modeled mobility channels. This suggests that the positive effect may be of a different nature than the negative effect. For instance,

Table 15: IV regressions on wages at the city-industry level (2-year growth effects)

Dependent variable: 2-year growth in wages of non-migrants				
	(1)	(2)	(3)	(4)
Wage level	-0.433***	-0.708***	-0.476***	-0.845***
	(0.022)	(0.026)	(0.025)	(0.025)
Employment level	0.028***	0.059***	0.023**	0.057***
	(0.009)	(0.011)	(0.009)	(0.013)
US migration	-0.024***	-0.027**	-0.023***	-0.029**
	(0.006)	(0.01)	(0.006)	(0.013)
F-test (first stage)	94.1	25.1	75	15.9
Dummies		c	i	c,i
Observations	4271	4271	4271	4271

*City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area-occupation. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

if the effect is mainly due to knowledge spillovers, the relatively slow dissipation across cities and industries suggests that knowledge does not diffuse very easily geographically or from one industry to the other.

On balance, do the positive wage effects in a city-industry dominate the negative ones? To determine this, Table 15 reruns our wage analyses once more, but now at the city-industry level. Note that this aggregation considers all workers in a city-industry cell to be the same, regardless of their occupation. The results suggest that the *average* worker in a city-industry cell is affected negatively by return migrants.

4.3 Reinterpreting employment-growth effects

The dissipation pattern of wage effects is most in line with a scenario in which workers more easily move between regions than between industries or occupations. This contradicts our earlier conclusion from the employment regressions. There, the finding that returnees do not destroy but create jobs for locals, led us to conclude that it is easiest for workers to move between industries. This leaves us with a puzzle: why would employment grow faster in industries receiving returnees, if workers predominantly move across cities in response to a return migration shock?

We consider three potential explanations. First, while mobility across regions appears to be the primary mechanism of adjustment, we cannot exclude that some inter-industry labor mobility takes place that generates Rybczynski effects. In section 4.3.1, we will test this hypothesis empirically. Second, it is theoretically possible that local labor market imbalances are adjusted by migration into, as opposed to, out of, the affected city. In section 4.3.2, we show that there are scenarios imaginable under which the affected city-industry increases employment, even when the only adjustment channel is geographical mobility. Third, returnees could bring with them productive knowledge. The temporary boost in productivity might also explain the observed wage dynamics, as well as why we see employment in a city-industry increase.

4.3.1 Industry mobility and Rybczynski effects

The wage regressions force us to revisit our conclusions on returnees' effect on employment growth. Our original explanation for this growth is based on standard Heckscher-Ohlin dynamics. In a Heckscher-Ohlin world, city-industries may expand due to the Rybczynski effect: an inflow of workers in occupations that are intensively used in an industry leads to a more than proportional expansion of employment in that industry. The Rybczynski effect operates through inter-industry mobility of workers. However, our wage regressions point to mobility between cities, not industries as the most important adjustment channel. This makes it implausible that the observed employment effect of return migration is entirely – or even predominantly – due to Rybczynski effects.

To assess how much of the employment-growth effects can be attributed to Rybczynski effects, we once again exploit the occupational dimension of our data. In particular, unlike knowledge spillovers, Rybczynski effects operate through changes in the relative price of differently skilled workers in a local labor market. Therefore, they should depend on the relative abundance of workers with a given set of skills in the city, not in the city-industry. This suggests that we can gauge the importance of Rybczynski effects by determining how well the occupational composition of returnees in a city matches each industry's skill requirements. We proxy this match as follows:

$$Ryb_{ci} = \sum_{o} T_{io} M_{co}, \tag{13}$$

where T is a technology matrix (how intensive is industry i's production function in occupation o?) and M is a migration matrix (how many returnees with experience in occupation o arrive in city c?). The technology matrix is based on the Bureau of Labor Statistics' 2004 industry-occupation matrix. The migration matrix is based on EMIF Norte (devueltos) for the years 2006 and 2007.[22]

The Rybczynski effect states that, if an industry is relatively intensive in certain occupations and a city receives a relatively high inflow of returnees with experience in those occupations, the employment in the city-industry will grow. In line with this, we construct the technology matrix in relative terms, using the Balassa Index.[23] Next, we regress the long-term (i.e., five-year) employment growth in city-industries on both the number of returnees in that city-industry and on the Rybczynski indicator of eq. (13). Because our identification strategy is insufficiently strong to instrument both variables, we run this regression in OLS.[24] Table 16 reports the results.

The Rybczynski indicator has indeed a positive effect on employment growth, with an estimated elasticity of about 2%. However, the effect is statistically significant only at the 10% level. Meanwhile, the estimated elasticity to return migration remains unchanged. This suggests that although Rybczynski effects do seem to operate, they cannot account for the employment-growth effects we reported earlier.

4.3.2 Modeling city mobility

If Rybczynski effects cannot explain the observed employment effects, can such effects emerge in a model without inter-industry mobility? In section 2, we showed that migration shocks m_{cio} create an imbalance in the occupational employment ratios between cities. The local economy of city c can

[22] Details on the data harmonization behind and the creation of these matrices are provided in appendix C.3.

[23] We explore variations of this (for instance, making T a share and not a Balassa Index, or making inflows of migrants in a city-occupation relative too) and find consistent results. See Tables A.4 and A.5 in appendix.

[24] We report the results of 2SLS in appendix in table A.6. Results are consistent in regressions where we have a strong first stage.

Table 16: Rybczynski effects

OLS - Dependent variable: employment growth '07-'12								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
US returnees	0.016***	0.014***	0.013***	0.011***	0.018***	0.017***	0.012***	0.011***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Ryb		0.027***		0.053***		0.025**		0.03***
		(0.008)		(0.011)		(0.01)		(0.011)
Observations	3494	3494	3494	3494	3494	3494	3494	3494
Industry dummies	N	N	Y	Y	N	N	Y	Y
City dummies	N	N	N	N	Y	Y	Y	Y

*Cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively. Regressions (1)–(3) control for industry and city growth of employment, instead of using dummies. All variables in logarithm*

be brought back to equilibrium by migration either *out of* the affected occupation ϕ, or *into* the unaffected occupation, ω, in industry i. Both of these responses (and all intermediate combinations) would yield valid equilibria. Therefore, we argued before that there is no particular reason to expect the imbalance to unwind in one direction or the other. Here, we re-examine this claim by introducing a migration equation[25] that allows us to determine what is the most likely direction of net migration flows. Keeping things as simple and generic as possible, we write the flow rate to city 1 for each occupation as:

$$\begin{aligned} \dot{L}_{1i\phi} &= -\dot{L}_{2i\phi} = \delta log\left(\frac{w_{1i\phi}}{w_{2i\phi}}\right) \\ \dot{L}_{1i\omega} &= -\dot{L}_{2i\omega} = \delta log\left(\frac{w_{1i\omega}}{w_{2i\omega}}\right), \end{aligned} \tag{14}$$

where δ indicates the speed of the adjustment. We substitute for wages (equation (3)) and define $\Gamma \equiv (L_{1i\phi}/L_{1i\omega})/(L_{2i\phi}/L_{2i\omega})$ to write employment growth as

$$\dot{L}_{1i} = \dot{L}_{1i\phi} + \dot{L}_{1i\omega} = \delta(2\alpha - 1)log(\Gamma). \tag{15}$$

As long as the employment ratios are not adjusted (i.e., remain equal in the two cities) and given that the migration shock expands $L_{1i\phi}$, Γ will be greater than 1. The direction of net migration now depends on relative factor intensities. If $\alpha > 0.5$, workers in occupation ω will come to city 1. If, instead $\alpha < 0.5$, workers in occupation ϕ will abandon city 1 and move to city 2.

How likely is it that factor-intensity-dependent geographical migration can explain the observed city-industry employment growth? In fact, the empirical exercise in section 4.3.1 can be reinterpreted

[25] That is, we introduce an adjustment equation that captures how a system moves to an equilibrium. In the New Economic Geography literature (Ottaviano, 2007), such migration equations are common to determine which of multiple equilibria are most likely to be reached.

as an answer to this question. To see this, note that Ryb_{ci} can be regarded as a measure for the extent to which returnees to city-industry (c, i) are experienced in occupations that are used intensively by industry i. Therefore, if the observed employment effects were mostly due to workers migrating proportionally to factor-intensity induced occupational wage differences, we would expect that by adding Ryb_{ci} to the regression model, we would be able to account for some of the employment effects of return migration. The failure to do so therefore not only suggests that Rybczynski effects are an insufficient explanation for our empirical findings so far, but also that a pure factor-intensity explanation for the direction of equilibrium-restoring migration dynamics cannot fully account for them.

4.3.3 Knowledge spillovers

A third explanation for the positive employment effects of return migration is knowledge spillovers. Knowledge spillovers are typically associated with high skilled migrants, not with the relatively low-skill employment categories in which the returnees in our study are experienced. However, we conjecture that the high-skill versus low-skill dichotomy ignores an important dimension of return migration: since productivity in the U.S. is presumably higher than in Mexico across many activities, immigrants may acquire useful knowledge even in rather low-tech industries or low-skill occupations. Upon their return, the industry-specific knowledge acquired in a frontier economy like the U.S. may be of great value to the local economy in the returnees' home countries.

Following Moretti (2004), we model migration related knowledge-spillovers as a shift of technology in the productive unit that receives the return migrants, $\theta_{ci} = f(m_{ci})$, yielding the following equation for wages:

$$w_{ci\phi} = P_i \theta_{ci} L_{ci\phi}^{\alpha_i - 1} L_{ci\omega}^{1-\alpha_i} \alpha_i. \tag{16}$$

Equation (16) shows how knowledge spillovers would counteract (temporary) wage declines that result from substitution effects. The net effect of migration on wages now depends on the relative magnitudes of these countervailing forces.

Note that it is implausible that knowledge spillovers would permanently raise productivity in a city-industry cell. If they would, producers in city 1 could permanently have larger margins and offer higher wages, which would eventually lead to a full concentration of the affected industry (say A) in city 1. In a more realistic scenario, knowledge spillovers will give local firms a temporary edge. In the longer run, firms in other cities could acquire the technology of city 1, or firms in city 1 could open new establishments in city 2 to exploit the lower wages. Moreover, if return migration is able to diffuse frontier technologies from the U.S. to Mexico, there is no reason to believe that internal migration could not diffuse this technology further throughout Mexico.

In a scenario with knowledge spillovers, temporary technological differences and temporary imbalances in factor intensity would simultaneously determine the adjustment trajectory of employment distribution of industry i across the two cities. We can shed light on this adjustment trajectory, by rewriting the migration equation in (15) to allow for differences in technology θ_{ci}:

$$\dot{L}_{1i} = 2log\left(\frac{\theta_{1i}}{\theta_{2i}}\right) + \delta(2\alpha - 1)log(\Gamma). \tag{17}$$

Equation (17) shows that – even in the presence of negative factor-intensity forces ($\alpha < 0.5$) – a positive, but temporary, technology shock could reverse the net equilibrating migration flow between city 1 and city 2, leading to a permanent increase in employment in city-industry (c, i). This explanation aligns most closely with our empirical findings. It would explain (1) why we see permanent positive employment effects in city-industries that receive return migrants, in spite of the evidence that geographical mobility is the most important channel for the local economy to adjust to these return migrants; (2) why wages of unaffected occupations in the city-industry tend to rise; and (3) why positive wage effects dissipate along different channels than negative wage effects.

5 Conclusions

US return migration has had mixed effects on locals who had never left Mexico. In the short run, these locals experience negative wage effects from being substituted by returnees in occupations in which the returnees find employment. However, in other occupations, local workers may see their wages go up. This positive effect is highly localized: it is limited to locals who work in the same city-industry as, but different occupations than, the returnees. In the long run, a more clear-cut picture emerges. Wage effects – negative as well as positive – fade out almost completely within five years from the arrival of returnees. In contrast, returnees cause employment in the city-industry in which they arrive to expand permanently. In other words, whereas in the short run, return migration creates winners and losers among locals, in the long run, the returnees create jobs by inducing growth in industries in which they had previously worked in the U.S..

5.1 Aggregate effects: a back-of-the-envelope calculation

What do these findings mean for the impact on the Mexican economy as a whole? To get a sense of this, consider the following back-of-the-envelope calculation of the monetary value of the permanent growth in employment opportunities that was induced by the spike in Mexican return migration between 2006 and 2007.[26] This spike represented a roughly 30% increase in return migration over previous years (some 60,000 additional returnees). If we distribute this increase proportionally across existing city-industries and use the about 7% elasticity from our IV models in Table 8 as the employment effect of these returnees, we find that the increase in return migration created 800,000 jobs. Next, we multiply this by the average annual wage in each city-industry in 2012. This yields a gross value of around 2 billion USD (2012 USD), or .2% of Mexico's GDP in 2012. Note, however, that this assumes that all new jobs are filled by workers who had previously been unemployed or inactive and that none of the new jobs are filled by poaching workers from other city-industries. This is obviously unrealistic. The net value of the jobs that returnees create will therefore be substantially lower than 2 billion USD. Furthermore, at its peak, the net negative effect of returnees on local wages was also about 2 billion USD.[27] Although these effects seemingly disappear over time, this may just mean that they have been washed out across the Mexican population. Moreover, returnees themselves incur heavy wage losses.[28] With 60,000 returnees, we estimate that such losses amount to roughly 500 million USD.[29] Moreover, some of these income losses are felt by family members of returnees in Mexico as a drop

[26]Note that, our log-log regression models force us to look at the increase in return migration over a certain (non-zero) base return migration.

[27]This uses an 6% wage elasticity as suggested by the findings in Table 13 in affected city-occupations.

[28]Given that most returnees were forced to move back to Mexico, these wage losses will also represent losses in utility.

[29]Based on a comparison of wages in IPUMS and Mexican census, we find that Mexican wages are about a fourth of US wages, for workers with primary education or less (which is the majority of the sample; the loss is between 1/3 and 1/2 for workers with secondary or tertiary education), meaning that returnees lose about 75% in nominal wage

in remittances that totals about 200 million USD.[30] Given that each of these welfare components is large and uncertain, on balance the aggregate effects on the Mexican economy remain hard to gauge. However, what is clear is that the flow of return migrants creates winners as well as losers in the Mexican economy.

5.2 Wider implications

Our analysis also sheds light on the wider immigation debate in economics. First, we find evidence that migration affects local wages, but that such effects are easily overlooked in cross-sectional analyses or in analyses that take a too long time horizon. To be precise, we find that wage effects peak between two and three years and all but fully vanish within five years from the arrival of return migrants. These wage effects dissipate mostly across space. This supports the contention of Borjas et al. (1996) that spatial counterfactuals should be treated with caution: regions that are not directly affected by return migrants may still be indirectly affected through the internal migration flows these returnees set in motion.

Second, wage effects of return migration are not uniformly negative. Some workers even experience wage increases due to the arrival of returnees. However, these positive wage effects are only visible within the city-industry (the "productive unit") in which returnees arrive. This highlights the importance of carefully distinguishing among different worker groups when researching immigration effects. Although we cannot unambiguously determine whether these positive effects are due to complementarities between returnees and locals or due to knowledge spillovers, we believe that the overall evidence favors the latter explanation. If this is true, the typical distinction in migration debates between low-skill and high-skill migrants – where the former are supposedly a boon and the latter a burden to the host economy – is inadequate. What matters is not the skill level of immigrants, but rather the skill *gradient* between sending and recipient country and the *type* of skills and know-how of the immigrants. In this context, returnees are a particularly interesting group of migrants. Not only should returnees face relatively few linguistic and cultural barriers when integrating into the local labor market. The ones who have worked in a technologically more advanced economy may also bring back useful knowledge regardless of the positions they held or the industry in which they worked.

Finally, the evolution of wage effects suggests that local workers most easily respond to wage differentials by moving between cities, not across occupations or industries. This suggests that it is easier for workers to relocate than to retrain in order to acquire new skills. Moreover, the apparent lack of mobility of workers across industries suggests that human capital does not only have an occupation-specific component, but also an industry-specific one. This notion is corroborated in the finding that positive complementarity or spillover effects materialize only within a city-industry-occupation cell, not within a city-occupation cell.

However, the most robust finding in our paper is that circular migration can cause structural change in home countries. In the case of Mexico-U.S. migration, a large portion of Mexican immigrants spends formative years of their working lives in the U.S.. These immigrants – while on the surface relatively unskilled – learn their trade in a particular industry and occupation in the U.S.. When they return to Mexico they bring home skills and knowledge that helps Mexican industries grow. Although the welfare implications of this growth are ambiguous, return migration unambiguously triggers a transformation of the industry mix across Mexican cities.

[30]This estimate is based on the share in total annual remittances to Mexico (24 billion in 2012 USD) attributable to 60,000 Mexican immigrants in the U.S..

References

Akcigit, U., Grigsby, J., and Nicholas, T. (2017). Immigration and the rise of American ingenuity. *American Economic Review*, 107(5):327–31.

Ambrosini, J. W. and Peri, G. (2012). The determinants and the selection of Mexico–US migrants. *The World Economy*, 35(2):111–151.

Bahar, D., Özgüzel, C., Hauptmann, A., and Rapoport, H. (2019). Migration and post-conflict reconstruction: The effect of returning refugees on export performance in the former Yugoslavia. IZA Discussion Paper 12412, IZA.

Bahar, D. and Rapoport, H. (2018). Migration, knowledge diffusion and the comparative advantage of nations. *The Economic Journal*, 128(612):F273–F305.

Beine, M., Docquier, F., and Rapoport, H. (2008). Brain drain and human capital formation in developing countries: winners and losers. *The Economic Journal*, 118(528):631–652.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics*, 118(4):1335–1374.

Borjas, G. J., Freeman, R. B., Katz, L., et al. (1996). Searching for the effect of immigration on the labor market. *American Economic Review*, 86(2):246–51.

Borjas, G. J. and Katz, L. F. (2007). The evolution of the Mexican-born workforce in the United States. In Borjas, G. J., editor, *Mexican immigration to the United States*, pages 13–56. University of Chicago Press and NBER.

Card, D. (1990). The impact of the mariel boatlift on the miami labor market. *ILR Review*, 43(2):245–257.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64.

Card, D. and Lewis, E. G. (2007). The diffusion of Mexican immigrants during the 1990s: Explanations and impacts. In Borjas, G. J., editor, *Mexican immigration to the United States*, pages 193–228. University of Chicago Press and NBER.

Chiquiar, D. and Hanson, G. H. (2005). International migration, self-selection, and the distribution of wages: Evidence from Mexico and the United States. *Journal of Political Economy*, 113(2):239–281.

Choudhury, P. (2015). Return migration and geography of innovation in MNEs: a natural experiment of knowledge production by local workers reporting to return migrants. *Journal of Economic Geography*, pages 585–610.

Clemens, M. A., Lewis, E. G., and Postel, H. M. (2018). Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion. *American Economic Review*, 108(6):1468–87.

Conover, E., Khamis, M., and Pearlman, S. (2018). Reversed migration trends and local labor markets.

Diodato, D. (2018). A network-based method to harmonize data classifications. Papers in Evolutionary Economic Geography 1843.

Duranton, G. and Puga, D. (2005). From sectoral to functional urban specialisation. *Journal of urban Economics*, 57(2):343–370.

Dustmann, C. and Glitz, A. (2015). How do industries and firms respond to changes in local labor supply? *Journal of Labor Economics*, 33(3):711–750.

Dustmann, C., Schönberg, U., and Stuhler, J. (2016). The impact of immigration: Why do studies reach such different results? *Journal of Economic Perspectives*, 30(4):31–56.

Gathmann, C. and Schönberg, U. (2010). How general is human capital? a task-based approach. *Journal of Labor Economics*, 28(1):1–49.

Hausmann, R. and Nedelkoska, L. (2018). Welcome home in a crisis: Effects of return migration on the non-migrants' wages and employment. *European Economic Review*, 101:101–132.

Hornung, E. (2014). Immigration and the diffusion of technology: The Huguenot diaspora in Prussia. *American Economic Review*, 104(1):84–122.

Kambourov, G. and Manovskii, I. (2009). Occupational specificity of human capital. *International Economic Review*, 50(1):63–115.

Kerr, W. R. and Lincoln, W. F. (2010). The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics*, 28(3):473–508.

Leamer, E. E. (1995). The Heckscher-Ohlin model in theory and practice. Princeton Studies in International Finance 77.

McKenzie, D. and Rapoport, H. (2010). Self-selection patterns in mexico-us migration: the role of migration networks. *The Review of Economics and Statistics*, 92(4):811–821.

Moretti, E. (2004). Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics*, 121(1):175–212.

Moser, P., Voena, A., and Waldinger, F. (2014). German Jewish émigrés and US invention. *The American Economic Review*, 104(10):3222–3255.

Ottaviano, G. I. (2007). Models of "new economic geography": factor mobility vs. vertical linkages. In Fingleton, B., editor, *New Directions in Economic Geography*, chapter 2, pages 53–69. Edward Elgar Cheltenham, UK.

Ottaviano, G. I. and Peri, G. (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association*, 10(1):152–197.

Reinhold, S. and Thom, K. (2013). Migration experience and earnings in the Mexican labor market. *Journal of Human Resources*, 48(3):768–820.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., and Sobek, M. (2019). *IPUMS USA: Version 9.0 [dataset]*. Minneapolis, MN: IPUMS, 2019. https://doi.org/10.18128/D010.V9.0.

Saxenian, A. (2007). *The New Argonauts: Regional Advantage in a Global Economy*. Harvard University Press, Cambridge MA.

Spolaore, E. and Wacziarg, R. (2009). The diffusion of development. *The Quarterly Journal of Economics*, 124(2):469–529.

Sullivan, P. (2010). Empirical evidence on occupation and industry specific human capital. *Labour Economics*, 17(3):567–580.

The Economist (2014). Ready, steady, do nothing. *The Economist*, 13th September 2014.

The World Bank (2016). *Migration and Remittances Factbook 2016, 3rd edtion.* Washington, DC: World Bank. doi:10.1596/978-1-4648-0319-2.

Appendix

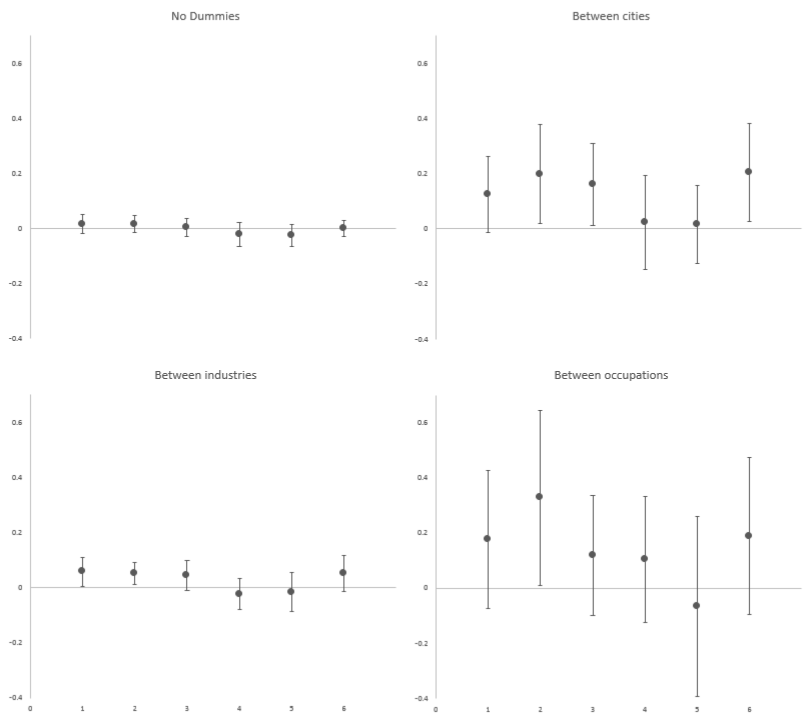
A Robustness and additional output

Table A.1: IV regressions robustness - impact on employment

IV - Dependent variable: employment growth (5-year)					
dataset		(1)	(2)	(3)	(4)
Baseline	US returnees	0.076***	0.097***	0.092***	0.063**
		(0.016)	(0.027)	(0.019)	(0.031)
	F-test	78	20.6	62.5	12.4
Excluding rural areas	US returnees	0.052***	0.065***	0.067***	0.03
		(0.016)	(0.024)	(0.019)	(0.026)
	F-test	40.4	12.8	36.1	8.5
Excluding border states	US returnees	0.035**	0.069***	0.048**	0.048
		(0.015)	(0.024)	(0.019)	(0.03)
	F-test	36.5	11.9	27.4	6.7
Low epsilon (1e-5)	US returnees	0.057***	0.071***	0.069***	0.047**
		(0.012)	(0.02)	(0.014)	(0.023)
	F-test	74.3	19.6	58.9	11.6
High epsilon (1)	US returnees	0.146***	0.203***	0.165***	0.141***
		(0.026)	(0.044)	(0.03)	(0.05)
	F-test	123.9	33.9	103.3	24.2
Log-level	US returnees	0.0007***	0.0013***	0.0007***	0.0006**
		(0.0002)	(0.0004)	(0.0003)	(0.0003)
	F-test	18.6	12.7	17.2	10.8
Dummy Approach	US returnees	0.999***	1.214***	1.235***	0.84*
		(0.217)	(0.365)	(0.269)	(0.438)
	F-test	63.9	17.1	49.5	9.6
Share of returnees	US returnees	0.453***	0.674***	0.603***	0.619
		(0.1)	(0.236)	(0.144)	(0.411)
	F-test	48.6	9.8	33.1	3.4
Industry dummies		N	Y	N	Y
City dummies		N	N	Y	Y

*City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

Figure A.1: Dynamics of wages at the city-industry-occupation level. Effect on other occupations in the same city-industry



Estimated impact of return migration on different time horizons. The horizontal axis represents T, the number of years over which growth is computed (between 2007 and 2007+T). The vertical axis the estimated elasticity of returnees. Vertical bars: 95% confidence interval.

Table A.2: IV regressions on wages at the city-occupation level (3-year growth effects)

Dependent variable: growth in wages of non-migrants				
	(1)	(2)	(3)	(4)
Wage level	-0.689***	-0.708***	-0.751***	-0.766***
	(0.048)	(0.06)	(0.082)	(0.103)
Employment level	0.135***	0.16***	0.198**	0.206*
	(0.048)	(0.06)	(0.082)	(0.103)
US migration own occupation	-0.065*	-0.09***	-0.038	-0.043***
	(0.039)	(0.03)	(0.026)	(0.012)
US migration other occupation	-0.003	-0.196	-0.027	-0.16
	(0.022)	(0.236)	(0.032)	(0.189)
F-test (first stage)	37.02	2.71	11.8	3.04
Dummies		c	o	c,o
Observations	1674	1674	1674	1674

*Cluster robust standard errors in parentheses (dummy dependent). Cross-section: industry-metropolitan area-occupation. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

Table A.3: IV regressions on wages at the city-industry-occupation level (2-year growth effects)

Dependent variable: wage growth of non-migrants				
	(1)	(2)	(3)	(4)
Wage in occupation	-0.849***	-0.901***	-0.905***	-0.901***
	(0.034)	(0.041)	(0.044)	(0.037)
Employment in occupation	0.221***	0.017	0.332***	0.286***
	(0.034)	(0.041)	(0.044)	(0.037)
US migration in occupation	-0.107***	-0.169*	-0.06	-0.176***
	(0.035)	(0.089)	(0.128)	(0.054)
US migration in other occupations	0.021	0.24***	0.238	0.061**
	(0.016)	(0.091)	(0.242)	(0.023)
F-test (first stage)	7.33	4.61	4.12	7.54
Dummies		i,o	c,i	c,o
Observations	11193	11089	11021	10776

*Cluster robust standard errors in parentheses (dummy dependent). Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively.*

Table A.4: Rybczynski effects - variation with relative tehnology.

OLS - Dependent variable: employment growth '07-'12								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
US returnees	0.012***	0.011***	0.009***	0.008***	0.015***	0.014***	0.01***	0.01***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ryb		0.016**		0.036***		0.017*		0.009
		(0.008)		(0.011)		(0.009)		(0.012)
Observations	3493	3493	3493	3493	3493	3493	3493	3493
Industry dummies	N	N	Y	Y	N	N	Y	Y
City dummies	N	N	N	N	Y	Y	Y	Y

*The technology matrix T_{io} is here computed in relative terms: $T_{io} \equiv L_{io}/L_i$ instead of $T_{io} \equiv (L_{io}/L_i)/(L_o/L)$. City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively. Regressions (1)–(3) control for industry and city growth of employment, instead of using dummies. All variables in logarithm*

Table A.5: Rybczynski effects - variation with relative migration.

OLS - Dependent variable: employment growth '07-'12								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
US returnees	0.012***	0.012***	0.009***	0.009***	0.015***	0.015***	0.01***	0.01***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
l_specUS		0.007		0.016*		0.008		0.009
		(0.007)		(0.009)		(0.008)		(0.01)
Observations	3493	3493	3493	3493	3493	3493	3493	3493
Industry dummies	N	N	Y	Y	N	N	Y	Y
City dummies	N	N	N	N	Y	Y	Y	Y

*The migration matrix M_{co} is here computed in relative terms: $M_{co} \equiv m_{co}/m_c$ instead of $M_{co} \equiv m_{co}$. City-level cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively. Regressions (1)–(3) control for industry and city growth of employment, instead of using dummies. All variables in logarithm*

Table A.6: Rybczynski effects - 2SLS estimation

2SLS - Dependent variable: employment growth '07-'12								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
US returnees	0.07***	0.059***	0.098***	0.028	0.087***	0.083***	0.074*	0.046
	(0.014)	(0.015)	(0.031)	(0.031)	(0.017)	(0.019)	(0.039)	(0.038)
Ryb		0.018**		0.05*		0.009***		0.029**
		(0.01)		(0.013)		(0.012)		(0.012)
Observations	3494	3494	3494	3494	3494	3494	3494	3494
First-stage F	91.64	71.6	15.14	10.61	72.92	61.82	9.04	8.44
Industry dummies	N	N	Y	Y	N	N	Y	Y
City dummies	N	N	N	N	Y	Y	Y	Y

*Cluster robust standard errors in parentheses. Cross-section: industry-metropolitan area. Significance levels of 10%, 5% and 1% are marked by *, **, *** respectively. Regressions (1)–(3) control for industry and city growth of employment, instead of using dummies. All variables in logarithm*

B Additional information on data

B.1 Trends in migration

In this section, we clarify the method by which we constructed Figures 1 and 2 of this paper, depicting trends in migration between the U.S. and Mexico.

The migration flows out of the U.S. are taken directly from estimates provided by Pew research (https://www.pewresearch.org/hispanic/2012/04/23/appendix-a-additional-tables-and-chart/).

For the return flows, our core information comes from the EMIF Norte survey. Its publications provide yearly estimates of the total flow of returnees both voluntary and involuntary (deported). These estimates by themselves, however, are not fully satisfactory for two reasons: (1) for all years until 2009, they only include surveyed migrants who travel by land; (2) for voluntary returns, they include also those who are only coming back to Mexico for the short term. We adjust these raw estimates using information from an additional dataset that EMIF supplies since 2009: returns from the U.S. by plane. Using this data we can correct both shortcomings. For the first one we estimate $\gamma = (\sum_{t=2009}^{2013} N_t^P)/(\sum_{t=2009}^{2013} N_t^L)$, with N_t^P being the return flow by plane and N_t^L the one by land. We then predict the series of return by plane before 2009 by simply computing γN_t^L. Note that we calculate γ separately for voluntary returns and deported migrants. For the second issue, we exploit a question on this supplementary dataset that asks whether the reason of return is to move back to stay. About 4% of voluntary returnees with long-term residency in the U.S. declare they are traveling to settle back in Mexico. We deflate the series of voluntary returns accordingly.

As a sanity check, we look at the series of change in stock of Mexican-born residents in the U.S. (from Pew research) and we compare it with the net flows estimated with the series of out-migration and return migration and find them correlated ($R^2 = 0.44$,t=2.54) and with the same order of magnitude. Moreover, net migration turns negative at the same time.

B.2 ENOE

The main dataset in this paper is the ENOE (Encuesta Nacional de Ocupación y Empleo). This survey is held regularly since 2005[31] and, to match our period of interest, we collect data up until 2013. About 300,000 unique individuals (aged 12 or higher) are surveyed in every quarter. People who are selected for interview appear in the ENOE for 5 consecutive quarters before being dropped from the sample. Because of this feature, we expect in every quarter the entry of 60,000 new individuals in the sample and, in a single calendar year (which is the time unit we are interested in our analysis), 480,000 individuals. The actual number in the data is an average of almost 550,000 unique individuals per calendar year. This is due to higher re-sampling rate: with an average of 3.7 appearances in the ENOE, many individuals are dropped form the survey before the 5 quarters.[32]

As workers are often observed multiple times in a year, we need to weight each observation accordingly, that is we count each quarter observation 1/4. For instance, if a worker is observed three times in a year, once in industry A and twice in industry B, we will count her employment 0.25 in A and 0.5 in B. Note that these fractions of employment will be expanded using the factors provided in the ENOE itself.[33]

[31] Before this date, alternative surveys were used to track employment (e.g. Encuesta Nacional de Empleo, by INEGI).
[32] This happens for instance when one relocates.
[33] Roughly in line with the sampling rates, the mean expansion factor is 280.

C Harmonization of classifications

In this section, we discuss the geographical classification used in the analysis as well as the harmonization the industry and occupation classifications we applied in our work. In the analysis in this paper we combine industry data, sourced from Mexico and the United States in different periods. The North-American Industry Classification System (NAICS) allows in principle high compatibility between different our data. In practice, both Mexico and the US operate significant revisions between the 2002 and 2007 versions of NAICS. Moreover, the compatibility across NAICS countries varies for different industries. For instance, retail services are only comparable at 2-digit level among American, Mexican, and Canadian NAICS. Taking this into account, we build a raw concordance that links 3-digit industries in US-NAICS 2002, US-NAICS 2007, Mexico-NAICS 2002, Mexico-NAICS 2007. We then develop a methodology (described in Diodato, 2018) to transform this many-to-many mapping into a harmonized classification. The resulting classification, which we use throughout the paper, distinguishes among 64 industries. See appendix C.2 for more details. We use an analogous procedure for occupations. Over the period of analysis, the Mexican classification of occupations changed (from CMO to SINCO). Using the same method, we harmonize 3-digit CMO and SINCO into 27 occupational classes (see appendix C.3).

C.1 Geographical classification

We aggregate municipality-level data into *Zonas Metropolitanas* (ZMs), using a mapping provided by INEGI. These ZMs include only part of the country. We add the municipalities which are not included in a ZM by aggregating at the state level. As Distrito Federal is entirely included into ZM de Velle de México, there are 31 higher level entities to aggregate into.[34]

In our analysis, we use the 2010 definitions of Zona Metropolitanas. Even though the boundaries ZMs are routinely revised, by mapping municipality data in different years to this fixed 2010 definition we are able to keep consistent geographical boundaries over time. Also the many changes in municipal borders (mergers and splits) in the considered periods do not affect the consistency of these divisions, as we keep using the same mapping for the new areas.

C.2 Industry classification

We harmonize the NAICS classifications across Mexico and US, as well as across the 2002 and 2007 editions of NAICS, using a methodology capable of dealing with complex many-to-many mapping of industries. The methodology is described in more details in Diodato (2018), but we report here the core principle behind it. With many-to-many mapping across classifications, the only way to transform data without incurring in any error is to merge data on both sides of the concordance. If one tries instead to converge to one side (say to 2002 Mexican NAICS), one requires splitting 2007 data across the relevant industries, introducing errors.

Merging on both sides has the shortcoming that forces a loss of data detail. We propose and apply a compromise here where isolated links across classifications – which would result in considerable detail loss – are manually removed. We are very conservative in this approach and we remove only very few links:

- Wholesale and retail

[34] These rural entities are therefore composed of the state minus the ZMs. As ZMs boundaries go across states, we perform the subtraction state by state.

Table C.1: Mexican Zonas Metropolitanas (2010)

Code	Name	Code	Name
1	ZM de Aguascalientes	31	ZM de Monterrey
2	ZM de Tijuana	32	ZM de Oaxaca
3	ZM de Mexicali	33	ZM de Tehuantepec
4	ZM de La Laguna	34	ZM de Puebla-Tlaxcala
5	ZM de Saltillo	35	ZM de Tehuacán
6	ZM de Monclova-Frontera	36	ZM de Querétaro
7	ZM de Piedras Negras	37	ZM de Cancún
8	ZM de Colima-Villa de Álvarez	38	ZM de San Luis Potosí-Soledad de Graciano Sánchez
9	ZM de Tecomán	39	ZM de Rioverde-Ciudad Fernéndez
10	ZM de Tuxtla Gutiérrez	40	ZM de Guaymas
11	ZM de Juárez	41	ZM de Villahermosa
12	ZM de Chihuahua	42	ZM de Tampico
13	ZM del Valle de México	43	ZM de Reynosa-Rio Bravo
14	ZM de León	44	ZM de Matamoros
15	ZM de San Francisco del Rincón	45	ZM de Nuevo Laredo
16	ZM de Moroleón-Uriangato	46	ZM de Tlaxcala-Apizaco
17	ZM de Acapulco	47	ZM de Veracruz
18	ZM de Pachuca	48	ZM de Xalapa
19	ZM de Tulancingo	49	ZM de Poza Rica
20	ZM de Tula	50	ZM de Orizaba
21	ZM de Guadalajara	51	ZM de Minatitlán
22	ZM de Puerto Vallarta	52	ZM de Coatzacoalcos
23	ZM de Ocotlán	53	ZM de Córdoba
24	ZM de Toluca	54	ZM de Acayucan
25	ZM de Morelia	55	ZM de Mérida
26	ZM de Zamora-Jacona	56	ZM de Zacatecas-Guadalupe
27	ZM de La Piedad-Pénjamo	57	ZM de Celaya
28	ZM de Cuernavaca	58	ZM de Tianguistenco
29	ZM de Cuautla	59	ZM de Teziutlán
30	ZM de Tepic		

  - MEX NAICS-2002 434 – MEX NAICS-2007 467
  - MEX NAICS-2002 468 – MEX NAICS-2007 436
  - MEX NAICS-2002 468 – MEX NAICS-2007 434

- Plastic and Ropes
  - MEX NAICS-2002 314 – MEX NAICS-2007 326
- Mining and mining services
  - MEX NAICS-2002 212 – MEX NAICS-2007 213
- Agricultural services and veterinary services
  - MEX NAICS-2002 541 – MEX NAICS-2007 115
- Real estate services and finance

Table C.2: Mexican states

Code	Name	Code	Name
101	Aguascalientes	117	Morelos
102	Baja California	118	Nayarit
103	Baja California Sur	119	Nuevo León
104	Campeche	120	Oaxaca
105	Coahuila de Zaragoza	121	Puebla
106	Colima	122	Querétaro
107	Chiapas	123	Quintana Roo
108	Chihuahua	124	San Luis Potosí
109	Ciudad de México*	125	Sinaloa
110	Durango	126	Sonora
111	Guanajuato	127	Tabasco
112	Guerrero	128	Tamaulipas
113	Hidalgo	129	Tlaxcala
114	Jalisco	130	Veracruz de Ignacio de la Llave
115	México	131	Yucatán
116	Michoacán de Ocampo	132	Zacatecas

** It is technically not a state, but a special administrative division. It is not in the analysis, as its activities are entirely captured by ZM 13*

  - US NAICS-2002 525 – US NAICS-2007 531

- Man and woman textile with other textile
  - US NAICS-2002 315 – US NAICS-2007 314

The resulting classification is shown in table C.3. Note that, since the 64 resulting classes are often the result of the merging of different underlying 3-digit classes, the names in table C.3 are based on our assessment. Industry 64 (retail, finance and insurance) is the most striking merge. For robustness we run the analysis excluding this category to find that results are unchanged.

C.3 Occupation classification

While for the harmonization of industry classifications we can rely on the NAICS common framework, occupations over time and across the US-Mexico border have stronger differences in the way they are binned. Mexican data use CMO classification (Clasificación Mexicana de Ocupaciones) until 2011/2013 (depending on the dataset), then change to SINCO (Sistema nacional de clasificación de ocupaciones). In the US, data are recorded with Standard Occupational Classification (SOC) system. The differences across the three systems are such that the merging system used for industries would aggregate data too much. To keep some detail, we opt for creating two separate concordances. One for the main regression, which only harmonizes the two Mexican system. The other, for the regression that needs to combine occupation-level data from the US (see Tables 16, A.4, A.5, A.6). Due to greater comparability across SOC and CMO, we get 27 classes in the first harmonization and 64 in the second.

Table C.3: Harmonized industries used in the analysis

Code	Name	Code	Name
1	Agriculture	33	Railway Transportation
2	Forestry	34	Water Transportation
3	Fishing, Hunting and Trapping	35	Truck Transportation
4	Support Activities for Agriculture and Forestry	36	Ground Passenger Transportation
5	Oil and Gas Extraction	37	Pipeline Transportation
6	Mining	38	Scenic and Sightseeing Transportation
7	Support Activities for Mining	39	Support Activities for Transportation
8	Utilities	40	Postal Services
9	Heavy and Civil Engineering Construction	41	Couriers and Messengers
10	Specialty Trade Contractors	42	Warehousing and Storage
11	Food Manufacturing	43	Publishing Industries)
12	Beverage and Tobacco Product Manufacturing	44	Broadcasting
13	Textile Product Mills	45	Telecommunications
14	Apparel Manufacturing	46	Real Estate and Construction
15	Leather and Allied Product Manufacturing	47	Rental and Leasing Services
16	Wood Product Manufacturing	48	Lessors of Nonfinancial Intangible Assets
17	Paper Manufacturing	49	Management of Companies and Enterprises
18	Printing and Related Support Activities	50	Professional, Scientific, and Technical Services
19	Petroleum and Coal Products Manufacturing	51	Waste Management
20	Chemical manufacturing	52	Educational Services
21	Plastics and Rubber Products Manufacturing	53	Hospitals
22	Nonmetallic Mineral Product Manufacturing	54	Social and Medical Assistance
23	Primary Metal Manufacturing	55	Performing Arts and Spectator Sports
24	Fabricated Metal Product Manufacturing	56	Museums, Historical Sites
25	Machinery Manufacturing	57	Accommodation
26	Computer and Electronic Products	58	Food Services and Drinking Places
27	Electrical Equipment and Appliance	59	Repair and Maintenance
28	Transportation Equipment Manufacturing	60	Personal and Laundry Services
29	Furniture and Related Product Manufacturing	61	Religious, Civic, Professional, Organizations
30	Miscellaneous Manufacturing	62	Household Services
31	Wholesale Trade	63	Other Public Services
32	Air Transportation	64	Retail, Finance and Insurance

Table C.4: Harmonized occupational classification: CMO & SOC

Code	Name	Code	Name
1	Top Executives	33	Communications Equipment Operators
2	Management Occupations	34	Business and Financial Operations Occupations
3	Computer and Mathematical Occupations	35	Information and Record Clerks
4	Architecture and Engineering Occupations	36	Dispatching, and Distributing Workers
5	Other, Life, Physical, and Social Science	37	Secretaries and Administrative Assistants
6	Life Scientists	38	Office and Administrative Support Occupations
7	Physical Scientists	39	Farming, Fishing, and Forestry Occupations
8	Life, Physical, and Social Science Technicians	40	Supervisors, Farming
9	Community and Social Services Occupations	41	Agricultural Workers
10	Religious Workers	42	Fishing and Hunting Workers
11	Social Scientists and Legal Occupations	43	Forest, Conservation, and Logging Workers
12	Postsecondary Teachers	44	Construction Trades Workers
13	Primary and Secondary School Teachers	45	Extraction Workers
14	Other Teachers and Instructors	46	Supervisors of Repair Workers
15	Other Education, Training, and Library Occ.	47	Vehicle Mechanics and Repairers
16	Art and Design Workers	48	Supervisors, Production Workers
17	Entertainers and Performers	49	Assemblers and Fabricators
18	Media and Communication Workers	50	Food Processing Workers
19	Arts, Entertainment, Sports, and Media	51	Metal Workers and Plastic Workers
20	Healthcare Practitioners and Technical Occ.	52	Textile, Apparel, and Furnishings Workers
21	Other Healthcare Support Occupations	53	Printing Workers and Woodworkers
22	Protective Service Occupations	54	Plant and System Operators
23	Supervisors, Food Preparation and Serving	55	Other Production Occupations
24	Food Preparation and Serving Workers	56	Supervisors, Material Moving Workers
25	Personal Care and Service Occupations	57	Air Transportation Workers
26	Funeral Service Workers	58	Motor Vehicle Operators
27	Personal Appearance Workers	59	Rail Transportation Workers
28	Building and Grounds Cleaning	60	Water Transportation Workers
29	Other Personal Care and Service Workers	61	Other Transportation Workers
30	Retail Sales Workers	62	Material Moving Workers
31	Sales Representatives	63	Military Specific Occupations
32	Other Sales and Related Workers	64	Unclassified Occupation

Table C.5: Harmonized occupational classification: CMO & SINCO

Code	Name	Code	Name
1	Scientific, Technical, Professional Occupations	15	Supervisors (IV - Restaurants)
2	Machine Operators	16	Writers, Journalists
3	Farmers	17	Musicians, Actors, Dancers
4	Industrial Laborers	18	Teachers in Special Schools
5	Teachers	19	Movers
6	Supervisor (I - Cultural)	20	Shop manager
7	Sailors	21	Preparation and Repair of Rubber and Plastic Products
8	Supervisor (II - Finance)	22	Airplane Pilots
9	Artists	23	Miners
10	University Professors	24	Construction Workers
11	Athletes	25	Other Transport
12	Commerce Occupations	26	Other Workers in Commerce
13	Supervisors (III - General)	27	Others
14	Conductors of Mobile Machinery		