Immigration and Wage Dynamics: Evidence from the Mexican Peso Crisis

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Abstract

What is the causal effect of low-skilled immigration on native wages? In spite of a vast literature on the wage effects of migration, no consensus yet exists. In this paper, I use the Mexican Peso Crisis of the mid-1990s, which raised net Mexican migration to the US by approximately 50 percent, as an exogenous push factor. I combine this novel push factor with the migration networks instrument widely used in the literature in order to study the short and long-run effects of immigration. In the short run, states that received large inflows of Mexican immigrants experienced substantial low-skilled wage declines: a 1 percent labor supply shock to a local labor market decreased wages of low-skilled US natives by 1-1.5 percent on impact. Within five years, these local shocks spread to the rest of the economy through net interstate labor reallocation. Fewer young low-skilled native workers migrated to the local labor markets shocked by Mexican immigration. The documented interstate reallocation implies that there are spillovers from high-immigration local labor markets to the rest of the economy, limiting the suitability of this natural experiment for evaluating longer-run impacts. Instead, I build a many-region model that depends on the two key parameters estimated in the short-run regressions: the local labor-demand elasticity and the sensitivity of internal reallocation to local shocks. Using these two parameters I calibrate my model to US state-level data. The model matches the documented patterns in the data and allows me to obtain the counterfactual wage evolution in the various local labor markets absent the immigration shock.

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1 Introduction

Despite the large inflows of immigrants into many OECD countries in the last 20 or 30 years, there is no consensus on the causal impact of immigration on labor market outcomes. Two reasons stand out. First, immigrants decide both where and when to migrate given the economic conditions in the source and host countries. Second, natives may respond by exiting or reducing inflows to the locations receiving these immigrants. The combination of these two endogenous decisions makes it hard to estimate the causal effect of immigration on native labor market outcomes.

Various strategies have been employed to understand the consequences of immigration on the labor market. Altonji and Card (1991) and Card (2001) compare labor market outcomes or changes in labor market outcomes in response to local immigrant inflows across locations. To account for the endogenous sorting of migrants across locations they use what has become known as the immigration networks instrument – past stocks of immigrants in particular locations are good predictors of future flows. They find only limited effects of immigration on labor market outcomes in the cross-section or in ten-year first differences: a 1 percent higher share of immigrants is associated with a 0.1-0.2 percent wage decline.[1] Also doing an across-location comparison, Card (1990) reports that the large inflow of Cubans to Miami in 1980 (during the Mariel Boatlift) had a very limited effect on the Miami labor market when compared to four other unaffected metropolitan areas.[2]

In contrast to Altonji and Card (1991) and Card (2001), Borjas et al. (1997) argue that local labor markets are sufficiently well connected in the US that estimates of the effect of immigration on wages using spatial variation are likely to be downward-biased because workers relocate across space. Instead, Borjas (2003) suggests comparing labor market outcomes across education and experience groups, abstracting from geographic considerations. Using this methodology with US decennial Census data between 1960 and 1990, he reports significantly larger effects of immigration on wages. A 1 percent immigration-induced increase in the labor supply in an education-experience cell is associated with a 0.3-0.4 percent decrease in wages on average. This has been the main controversy in the immigration debate: whether we should look at local labor markets or should instead focus on the national market.

This paper builds on this previous literature to better understand the effects of immigrants on labor market outcomes, by using the exogenous push factor of the Mexican Peso Crisis of 1995 in conjunction with the migration network instrument as my identification strategy. I show that the effect of immigration is large on impact for competing native workers – defined by skill and location groups – and that it quickly dissipates across space. My findings emphasize that in order to evaluate the labor market impacts of immigration it is crucial to think about time horizons and the dynamics of adjustment. These results help to reconcile previous findings in the literature.

In December 1994, the government led by Ernesto Zedillo allowed greater flexibility of the peso vis à vis the dollar. This resulted in an attack on the peso that caused Mexico to abandon the peg. It was followed by an unanticipated economic crisis known as the "the Peso Crisis" or the "Mexican Tequila Crisis" (Calvo and Mendoza, 1996). Mexican GDP growth fell 11 percentage points, from a positive 6 percent in 1994 to a negative 5 percent in 1995. This occurred while US GDP maintained a fairly constant growth rate of around 5 percent.

[1] Altonji and Card (1991) estimates using first differences between 1970 and 1980 and instruments result in a significantly higher effect. The same exercise, using other decades, delivers lower estimates, see Table 11 in this paper using differences between 1990 and 2000 and the same instrument Altonji and Card (1991) used.

[2] I discuss in detail the similarities and differences of this paper with Card (1990) in Section 3.8 and I provide a longer discussion in the Appendix.

This deep recession prompted many Mexicans to emigrate to the US. Precise estimates on net Mexican immigration are hard to obtain (see Passel (2005), Passel et al. (2012) or Hanson (2006)). Many Mexicans enter to the US illegally, sometimes escaping the count of US statistical agencies. However, as I show in detail in Section 2, all sources agree that 1995 was a high-immigration year.[3] As a result of the Mexican crisis, migration flows to the US were probably 50 percent higher, with around 200,000 more Mexicans immigrating in 1995 than in a typical year of the 1990s. This increase in the net Mexican inflows was a result of both more low-skilled – particularly young – Mexicans migrating to the US and fewer low skilled Mexicans returning to Mexico. I can thus use geographic, skill and labor market experience variation to see if workers more closely competing with these net Mexican inflows suffered more from the shock.[4]

Some concerns, however, remain. In the first place, in order to estimate the possible consequences of immigrants on native wages we need to know with whom Mexican workers, who are usually high school drop-outs, compete. Two elasticities of substitution are key to answer this: first, are natives and immigrants imperfect substitutes as suggested in Card (2009) and Ottaviano and Peri (2012)? And, second, are high school drop-outs and graduates imperfect substitutes as in Borjas (2003)? Importantly, the answer to these questions defines the pool of workers that absorbs new immigrant shocks.[5] In this paper I directly compare the labor market fortunes of natives and Hispanics or high school drop-outs and graduates in the years after the unexpectedly large Mexican inflow and show that they are all close substitutes.

A second concern is that, despite my efforts to combine all the data sources available, there is still some measurement error in the estimates of Mexican inflows. This could bias my estimates. To address it I use another natural experiment: the displacement of workers due to Hurricane Katrina.[6] In contrast to the case of undocumented low-skilled Mexican workers, it is unlikely that those displaced by Katrina are undercounted by statistical agencies. I obtain similar results for the effect of the Katrina migrants as for Mexican migrants, suggesting that mismeasurement of Mexican inflows is not severely biasing my estimates.

In this paper, I show that a 1 percent immigration-induced labor supply shock reduces low-skilled wages by around 1-1.5 percent in the two years following the shock.[7] Soon after, wages and unemployment shares return to their pre-shock trends. This is due to significant reallocation across states. While in the first year the immigration shock increases the share of low-skilled workers almost one to one in high-immigration states, in around two years it goes back to trend.[8] This is the case partly because fewer young native low-skilled workers move to high-immigration states. A 1 percent labor supply shock reduces the share of workers that moved to the affected locations from the rest of the nation by around .2 percentage points. This helps to understand why, while the effect on wages is large on impact, it quickly dissipates across states. By

[3] Using data from the 2000 US Census, from the US Department of Homeland Security (documented immigrants), estimates of undocumented immigrants from the Immigration and Naturalization Service (INS) as reported in Hanson (2006), estimates from Passel et al. (2012) and apprehensions data from the INS we see an unusual spike in the inflow of immigrants in 1995. I will discuss the numbers of immigration arrivals later in this paper.

[4] A similar instrumental strategy based on push factors and previous settlement patterns is used in Boustan (2010) study of the Black Migration.

[5] See Card (2009), Ottaviano and Peri (2012), Aydemir and Borjas (2011), Dustmann and Preston (2012), Borjas (2003) and Borjas and Katz (2007)

[6] In this case I can also use an adapted version of the immigration network instrument. Past stocks of workers from Louisiana and Mississippi – the two states that suffered the hurricane – are a good predictor of where displaced workers from Katrina moved. The identification strategy will thus interact this with the shock period, 2005 and 2006.

[7] I use unemployment shares, i.e., the number of unemployed divided by the working age population, instead of unemployment rates, because Current Population Survey data changed their questioning slightly in 1994 and because I do not consider the margin of moving out of the labor force.

[8] Over the 1990s the share of low skilled workers in high immigration states increased with immigration (Card et al., 2008). The reallocation documented in this paper explains how unexpected labor supply shocks are absorbed into the national economy. Changes in the factor mix absent unexpectedly large immigration-induced shocks can be explained trough technology adoption in Lewis (2012).

1999, the fifth year after the shock, wages of low-skilled workers in high-immigration states are only slightly lower than they were before the shock, relative to low-immigration states. Thus the US labor market for low-skilled workers adjusts to unexpected supply shocks quite rapidly.

Given that there are spillovers across states, I cannot use the natural experiment to investigate the longer-run effects of immigration on labor market outcomes. I take two avenues to try to shed some light on these longer-run effects. First, I show that, when abstracting from locations, the wage change between 1990 and 2000 for workers who entered the labor market in particularly high-immigration years during the 1990s is lower than for those who entered in lower immigration years, in line with what Oreopoulos et al. (Forthcoming) document for college graduates who enter the labor market in bad economic years. This is in the spirit of Borjas (2003) regressions but using the Peso Crisis as a factor generating exogenous variation in immigration inflows. Second, I introduce a spatial equilibrium model and calibrate it to US data to simulate the evolution of wages at the local level had the Peso Crisis not occurred. The model also allows me to interpret my reduced form estimates as structural parameters. Its two key parameters are the local labor demand elasticity and the internal migration sensitivity of native workers to local conditions. These, in turn, determine how much labor supply shocks are felt in wages and how fast these local shocks spread to the rest of the economy. In short, it helps to determine how long the long run is.

This paper contributes to two important literatures. First, it contributes to the understanding of the effects of low-skilled immigration in the US. Following the pioneering work by Card (1990) and Altonji and Card (1991), I use variation across local labor markets to estimate the effect of immigration. I extend their work by combining Card's immigration network instrument with the Mexican Peso Crisis as a novel exogenous push factor that brought more Mexicans than expected to many – and not just one as in Card (1990) – US local labor markets. This unexpectedly large inflow allows me to understand the timing and sequence of events in response to an immigration shock. When more immigrants enter specific local labor markets, wages decrease more than what is suggested in either Card (2001) or Borjas (2003). This prompts net interstate labor relocation that leads the shock to dissipate across space. This explains why in the longer-run, as I document, the effect of immigration on wages is small across local labor markets but larger across age cohorts (Borjas, 2003). This paper adds to Borjas (2003) longer-run results an instrumental variable strategy based on the age distribution of the unexpected inflow of Mexican workers resulting from the Mexican Peso Crisis.

Second, it contributes to the spatial labor economics literature. A number of recent papers look at the effects of negative shocks to the local labor demand using various strategies (see Autor et al. (Forthcoming), Autor et al. (2013b), Autor et al. (2013a), Beaudry et al. (2010), Hornbeck (2012), Hornbeck and Naidu (2012), Notowidigdo (2013), Diamond (2013)). In line with most spatial models (see Blanchard and Katz (1992) and Glaeser (2008)), they report how affected locations lose population after the shock. This labor reallocation becomes a labor supply shock to locations not directly affected. Thus, knowing how local labor markets respond to labor *supply* shocks helps in understanding how local labor *demand* shocks spread to the larger national labor market, an important and sometimes neglected aspect in these studies.

2 Historical background and data

2.1 A brief history of Mexican immigration

One of the most striking changes to US demographics in the last 20 years of the twentieth century is the large influx of immigrants from around the globe. Among those, an important fraction came from Mexico and were low-skilled (see Borjas and Katz (2007) or Passel et al. (2012)). In fact, the first wave of Mexican immigration started in the 1910s and ended with World War II. This brought almost one million Mexicans to the US who settled in neighboring US states, primarily Texas, Arizona, New Mexico and California (see Jiménez (2010) and Borjas and Katz (2007)). These early settlements established the basis for the formation of immigration networks that subsequently helped in posterior migration (Munshi, 2003).

After World War II migration started to decline, reaching its lowest levels (both in absolute terms and relative to US population) by the early 1970s. This dramatically changed in the 1980s. Mexican immigrant stocks increased to around two million in the early 1980s, to almost four million in the early 1990s and to around eight million in 2000. This makes the 1990s the highest immigration decade. Mexican immigration seems to have slowed in the beginning of the twenty first century, but it remains a controversial political topic, as can be seen in the immigration reforms that started in 2013 and the role it plays in every US presidential campaign.

2.2 Mexican Inflows in the 1990s

As reported in Borjas and Katz (2007), in 1990 the great majority of Mexicans were in California (57.5 percent), while the largest increases during the decade of the 1990s in the share of Mexicans in the state's labor force were in Arizona, Colorado, California, New Mexico and Texas. Within the 1990s, however, there was important variation in the number of Mexicans entering each year. There are a number of alternatives with which to try to obtain estimates on yearly flows between Mexico and the US. A first set of alternatives is to use various data sources to obtain a direct estimate of the Mexican (net) inflows. A second set of alternatives is to look at indirect data, like apprehensions at the US-Mexican border. I present these in what follows.

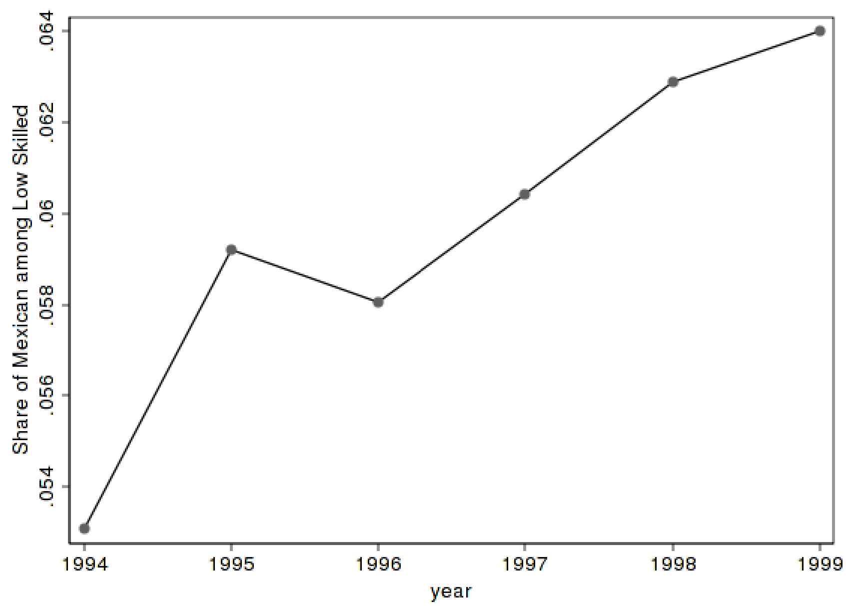
2.2.1 Direct measures of Mexican inflows

Perhaps the first natural source is the March Current Population Survey (CPS) from Ruggles et al. (2008). Unfortunately, the CPS only started to report birthplaces in 1994. Moreover, there are some concerns that the survey may have underestimated the unexpected inflow of Mexicans into the US in 1995. Despite these concerns, Figure 1 clearly shows that a significant number of Mexicans entered the US labor force in 1995. It is difficult to believe, given the net inflows of Mexicans during the 1990s suggested in the various sources that I will discuss in detail below, that the share of Mexicans in the low-skilled US workforce decreased in 1996.[9]

There are a number of ways to try to obtain better estimates than by exclusively using the CPS. To some extent they all rely on the question in the Census 2000: "When did this person come to live in the United States?" (Ruggles et al., 2008). This yields an estimate of the number of Mexicans still residing in the US in 2000 who arrived in each year of the 1990s. Figure 2 shows these estimates.

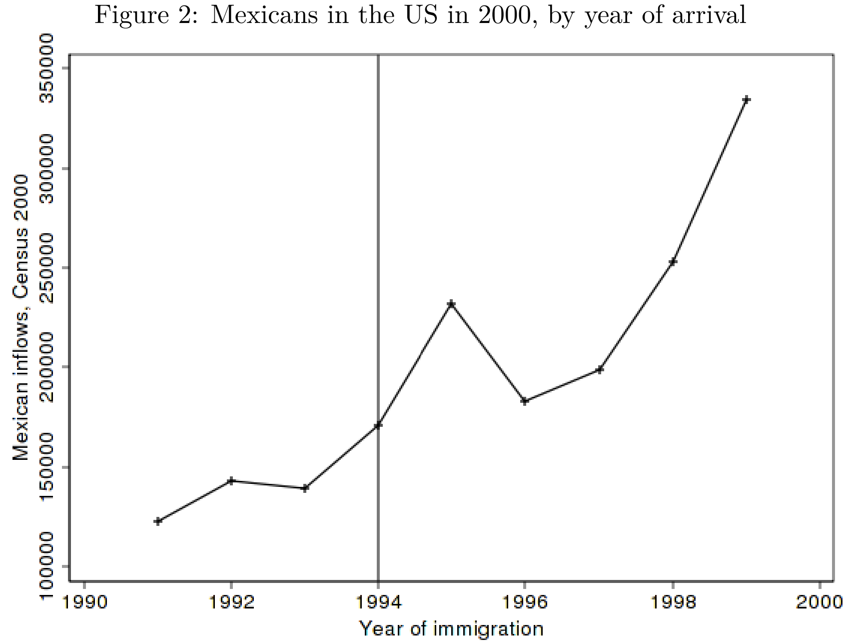
[9]Throughout the paper I define low-skilled workers as high school drop-outs and high school graduates.

Figure 1: Share of Mexicans in the US low-skilled labor force, CPS data



Notes: This figure plots the share of Mexicans among low-skilled workers in each year of the 1990s where CPS data is available. According to these data there was a labor supply shock in 1995 just less than 1 percent. Other data sets suggest that the shock might have been slightly larger.

Figure 2: Mexicans in the US in 2000, by year of arrival



Notes: This figure plots the number of Mexicans that were in the US in 2000 by their reported year of arrival in the US. Note that the number of Mexicans who reported 1995 as their arrival year is around 50 percent higher than those who reported 1994 or 1996.

The Census 2000 data in Figure 2 also document a spike in 1995. We observe an upward trend, partly the result of migrants who returned to Mexico or who died. How we account for this distinguishes the different estimates on annual inflows available in the literature. Passel et al. (2012) estimates are the standard source. For these estimates, they first compute aggregate net inflows over the 1990s by comparing stocks of Mexicans in 1990 and 2000 using US Census data. The net inflows over the 1990s is estimated at about 4-5 million and this needs to be matched by any estimates of yearly inflows.[10] To obtain the yearly inflows they use the US census question on year of arrival. Passel et al. (2012) adjust these estimates for undercount using information from the CPS and further inflate by 0.5 percent for each year before 2000 to account for mortality and emigration between arrival and 2000. Finally they match decade net inflows estimated using the 1990 and 2000 Censuses by further inflating the annual inflows by almost 9 percent. A summary of these numbers and of the Mexican counts of the US Censuses of 1990 and 2000 is provided in Table 1.

Table 1: Mexican Stocks and Inflows

Variable	**Source**	**Number**	**year**
Mexican Stock	US Cen. 2000	4,274,710	1990
Mexican Stock	US Cen. 1990	3,699,873	1990
Mexican Stock	US Cen. 2000 + Mex. Cen.	6,140,924	1995
		(=5,909,696+231,228)	
Mexican Stock	US Cen. 2000	7,970,009	2000
Average Inflow 1990-2000 (workers)	US Cen. 2000	369,529.9	1990-95
Average Inflow 1990-1995 (workers)	US Cen. 2000 + Mex. Cen.	373,242.8	1990-95
Average Inflow 1995-2000 (workers)	US Cen. 2000 + Mex. Cen.	365,817	1995-00
Mexican Inflow (total)	Passel et al. (2012)	400,000	1992
Mexican Inflow (total)	Passel et al. (2012)	370,000	1993
Mexican Inflow (total)	Passel et al. (2012)	430,000	1994
Mexican Inflow (total)	Passel et al. (2012)	570,000	1995
Mexican Inflow (total)	Passel et al. (2012)	490,000	1996
Mexican Inflow (total)	Passel et al. (2012)	470,000	1997
Mexican Inflow (total)	Passel et al. (2012)	600,000	1998

Notes: This table reports the stocks and inflows of Mexicans in the US in different years. Sources of the estimates are also reported. Data from Censuses comes from Ruggles et al. (2008). Further details are provided in the text.

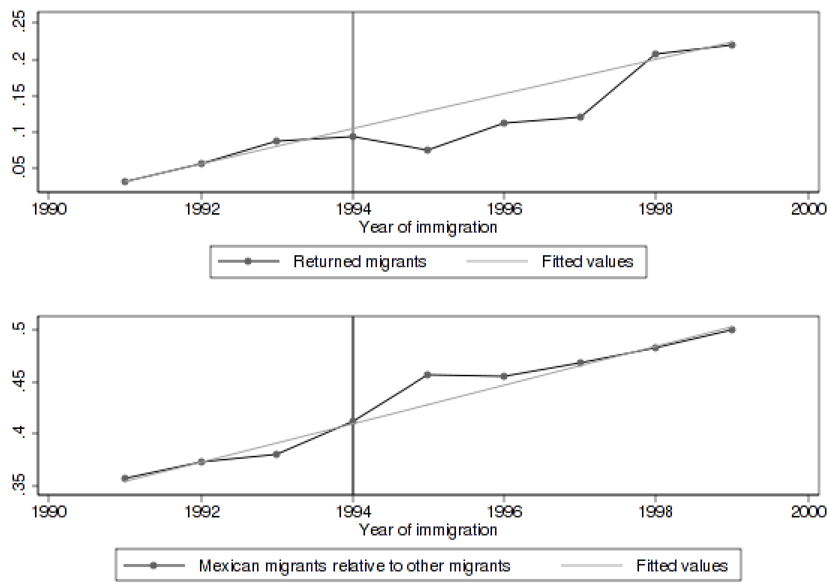
There are two concerns with Passel et al. (2012) estimates that I address. First, Passel et al. (2012) do not take into account the possibility that fewer Mexicans residing in the US returned to Mexico in particular years. Second, they do not account for the possibility that the observed spike in 1995 is just a result of the fact that 1995 is a multiple of 5 and thus, more commonly reported by respondents to US Census questioning, as suggested in Card and Lewis (2007). I try to address these two concerns by combining several data sources to propose an improved account of net yearly Mexican inflows.

To account for the possibility that fewer Mexicans than expected returned to the US when the crisis hit Mexico I use data from the Mexican Migration Project. The Mexican Migration Project is a survey intended research about the migration behavior of Mexicans. The survey is conducted both in Mexico and in the US and it is possible to use these data to construct the year of return of Mexicans that spent some time in the US during the 1990s and that were living in Mexico in the 2000s. The top panel of Figure 20 shows the share of these Mexicans by year of return. It clearly shows that fewer of them returned right after the Peso crisis hit. The upward trend is probably due to mortality and to the fact that there were fewer Mexicans in

[10] In the 2000 US Census, more Mexicans said that they arrived in the US in 1990 than the actual estimate in the 1990 US census. This suggests that undercount is an important issue or at least was in 1990. Hanson (2006) discusses the literature on counting undocumented migrants. There is some open debate on the size of undercount in 1990, but there is a wider consensus that the undercount is minimal in the 2000 US Census. Depending on the sources this implies a range of possible estimates of Mexican net inflows over the 1990s of between 4 and 5 million.

the US in the early 1990s (and thus fewer Mexicans returned to Mexico in the early 1990s than in the late 1990s simply because there were a smaller number of them in the US).

Figure 3: Yearly Mexican inflows and outflows measures



Note: The top panel shows the share of Mexicans residing in Mexico in the 2000s that claim to have returned to Mexico in the 1990s, by year of return. The lower panel shows the share of Mexicans residing in the US in each year of the 1990s, relative to immigrants from other destinations, using 2000 US Census information on the year of arrival of each individual. Taken together this evidence suggests that fewer Mexicans left the US and more entered as a consequence of the Mexican Peso Crisis.

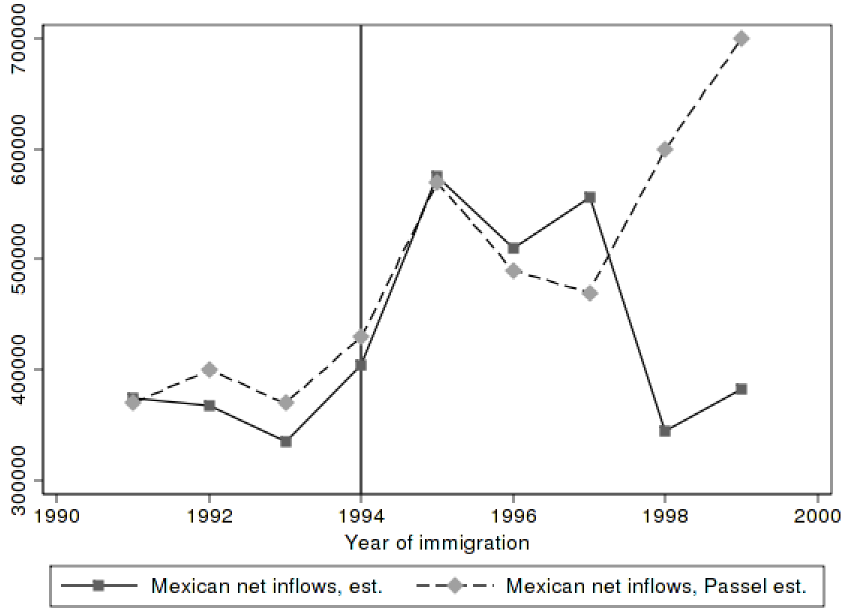
To obtain a measure of migration from Mexico, I use the question on year of arrival in the US in the 2000 US Census. Unlike Passel et al. (2012), to avoid concerns on artificial spikes in years that are multiples of five (Card and Lewis, 2007), I compute the number of Mexicans residing in the US each year relative to the number of low-skilled immigrants from the rest of the world using the aforementioned question in the 2000 US Census. This can be seen in the bottom panel in Figure 20. The upward trend in this figure is probably explained by the higher return rate of Mexican immigrants relative to immigrants of other nationalities.

In order to measure the actual net number of Mexicans migrating each year I do the following. I first de-trend the series of computed emigration and immigration from Mexico and in-migration presented in figure 20. I then use the percentage deviation from trend of these series to match the aggregate migration in the decade measured using the US Censuses in 1990 and 2000, following Passel et al. (2012). The gross numbers resulting from this exercise are summarized by Figure 4.[11]

In sum, the two graphs in Figure 20 show that more Mexicans moved to the US in 1995 and fewer returned to Mexico in 1995-1997. This increased the supply of low-skilled workers in particular states in the US, especially California. It is also reassuring that other data sources, like the number of legal Mexican migrants recorded by the Department of Homeland Security or the number of undocumented migrants

[11] In the Appendix I explain all the steps in more detail. The largest difference between my estimates and Passel et al. (2012) are 1998 and 1999. For instance, (Passel et al., 2012) reports that the net number of Mexican immigrants in 1999 was 700,000, while my estimates decrease this number to around 400,000. It is difficult to know with certainty which estimates are more accurate for these years. However, the fact that in the US census of 2000 350,000 answered that they moved to the US in 1999 suggests that my estimates might be more accurate than Passel et al. (2012) at least for 1999.

Figure 4: Net Mexican inflows into the US, by year



Notes: This figure shows the estimated net inflow of Mexicans by (Passel et al., 2012) and my own estimates using data from the US Census 2000 and the Mexican Migration Project.

computed using Immigration Naturalization Service data (Hanson, 2006) also see a spike right after the Peso Crisis. While all my qualitative results are robust to using any of the above measures, since the main source of identification comes from the unexpected large net inflow of 1995, measures underestimating the increase in net inflows will overestimate the effects of immigrants. I later discuss this concern in more detail; I address it by using the Katrina shock as an alternative natural experiment that unexpectedly brought more low-skilled workers to some US states.

To obtain a measure of the Mexican flows to each state at each point in time I first predict the place of arrival by the immigrant geographic distribution in 1990[12] and then, I assign the aggregate inflows accordingly. This is the measure that I use for the number of Mexicans arriving in state s at time t. It is worth noting that the measure I obtain and the one Passel et al. (2012) obtain are almost identical at the state level: the correlation between both is .98. This reflects the concentration of Mexicans in certain states.

2.2.2 Indirect measures of Mexican inflows

As mentioned before, we can also look at more indirect measures of Mexican inflows. A first such measure is the marked increase in "coyote" prices starting in 1995 – the price of the smuggler who facilitates migration across the Mexican-US border, see Hanson (2006). This may be in part due to increased border enforcement, but it also probably reflects an increased willingness to emigrate from Mexico. In fact, the US border enforcement launched two operations in the early 1990s to try to curb the number of immigrants entering the US. Operation Hold the Line and Operation Gatekeeper – launched in El Paso, TX and San Diego, CA respectively – had different degrees of success (Martin, 1995). Operation Hold the Line managed to

[12]Using the distribution in 2000 yields very similar results.

curb Mexican immigrants, while Operation Gatekeeper was less successful. To some extent, however, these operations redirected the routes Mexicans took to get to the US. There is some evidence suggesting that some of the Mexicans who would have otherwise entered through El Paso, TX did so through Nogales, AZ. In any case, the “coyote” prices only started to increase in 1995 and not when these operations were launched, suggesting that more people wanted to enter the US in 1995, right when the Peso Crisis hit Mexico, and that the increased “coyote” prices were not just a result of the increased border enforcement of the early 1990s.

Another piece of evidence suggesting higher inflows in 1995 is the evolution of the number of apprehensions over the 1990s (data from Gordon Hanson’s website, see Hanson (2006) or Hanson and Spilimbergo (1999)). Figure 5 shows the (log) monthly adjusted apprehensions. The spike in September 1993 coincides with the launching of Operation Hold the Line in El Paso, TX. At the beginning of 1995 there is a clear increase in the number of apprehensions that lasts at least until late 1996. This seems to coincide with the evolution of US low-skilled workers’ wages, as I will discuss in detail in what follows. Arizona and California saw much steeper declines in low-skilled wages in 1995 than Texas, something that seems consistent with the greater success of Operation Hold the Line.

Figure 5: Annual Mexican apprehensions in the US-Mexican border

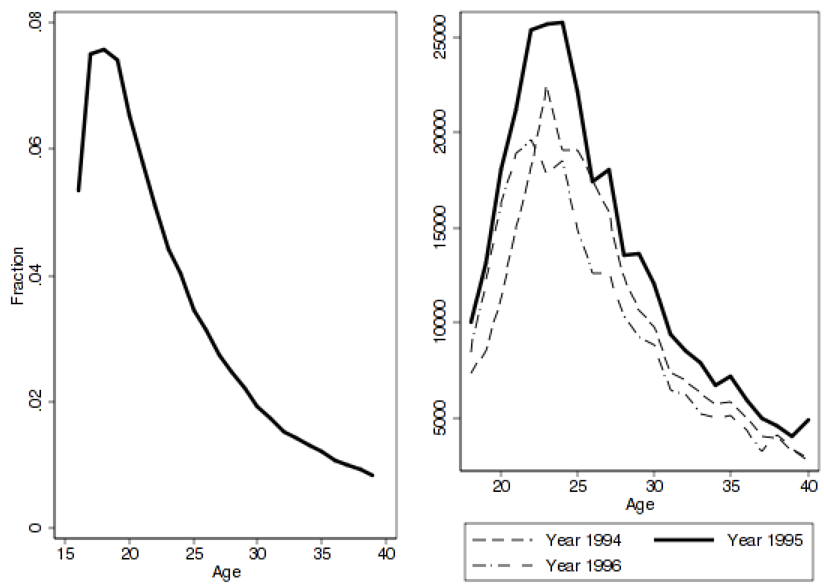
Note: This figure shows the (log) monthly apprehensions of Mexicans at the US-Mexican border. Month fixed effects are removed from the graph. Apprehensions data is highly cyclical, with most apprehensions occurring in the first few months of each year and less at the end of the year. Removing the month fixed effects helps visualize the longer run movements. Source: Hanson (2006).

2.3 Immigrant Age Distribution

All this evidence demonstrates both that more Mexicans entered the US and that fewer Mexicans already living in the US returned home in 1995. These Mexicans were probably mostly low-skilled (see Borjas and Katz (2007)), and they also differed (with respect to US natives) in their labor market experience. In this section I show how those new entrants were substantially younger.

Mexican immigrants tend to be young and compete with younger workers when they arrive in the US (see also Smith (2012)). The US Census of 2000 allows me to build the age distribution of the immigrants at the time of their arrival (at least of the Mexicans still in the US in 2000). To do so, I use information on the year of arrival and age in 2000. Figure 6 shows that most Mexican immigrants are indeed quite young when migrating to the US: around 80 percent of them are between 18 and 35 years old. As can be seen in the right panel of Figure 6, this is quite stable across years and it did not change in 1995 or 1996.

Figure 6: Age Distribution of Mexican Immigrants



Notes: The left hand side graph shows the average age of all Mexicans in the US in 2000 in the year of arrival to the US. The right hand side graph shows the age in 2000 of Mexicans in the US in 2000 in three selected years of arrival, 1994-1996. Around 90 percent of Mexicans are younger than 35 years old when arriving in the US and more Mexicans than usual immigrated to the US in 1995.

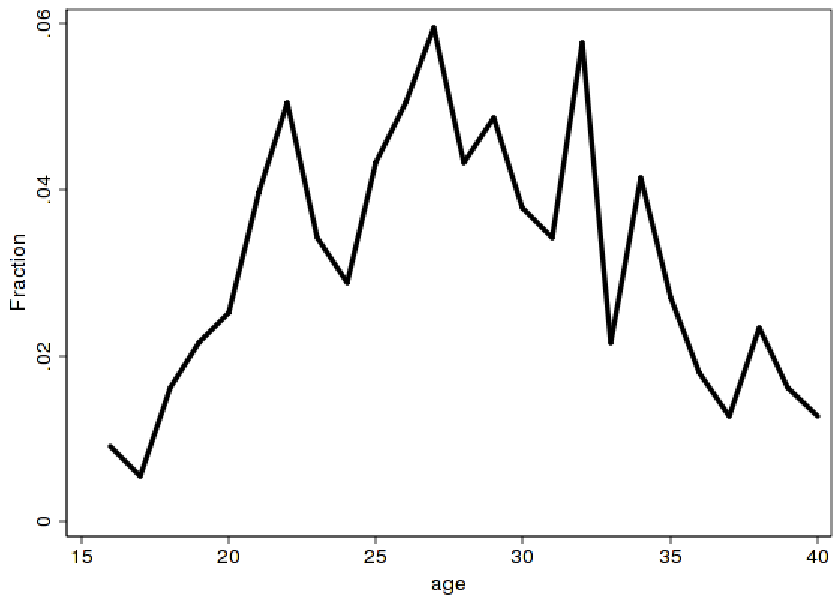
However, Mexican Migration Project data shows that Mexicans that returned to Mexico in the 1990s were more evenly distributed across age groups, as can be seen in Figure 7. Note that in this case the distribution is noisier because it is constructed using fewer observations than the ones in the 2000 US Census.

The information contained in Figures 6 and 7 suggests that although all low-skilled natives suffered a labor supply shock in 1995, this was disproportionately so for younger workers. This, as I show later on, matters for labor market outcomes and internal migration rates, as younger US native workers are seen to be more affected than older workers in 1995 in high-immigration states.

2.4 Geographic disaggregation

The geographic units that I use in this paper are, as should be clear at this point, US states. There is some discussion in the literature as to what is the appropriate geographic disaggregation to represent a local labor market. Card (2009) argues that metropolitan areas probably provide the appropriate level of analysis. When using Census data there are many metropolitan areas with many individual level observations. This is different with CPS data. As an example, there are only 11 metropolitan areas in the March CPS data for

Figure 7: Age Distribution of Returning Mexican Immigrants



Notes: This figure shows the age distribution of Mexicans that were living in the US in the 1990s and that returned to Mexico.

1995 that have more than 500 individual level observations. Another drawback of using metropolitan areas is that we would lose nearly 24,000 individual observations that lack metropolitan area information. This is a lot of information given the sample size in the CPS.

This suggests using a partition of the US territory, an observation also made in Autor and Dorn (2009). They use commuting zones (CZ), which are constructed based on commuting patterns from the 1990 US Census based on the work by Tolbert and Sizer (1996). This results in 722 different CZs that cover the entire US. The number of commuting zones, however, is too large for the CPS data. The CPS data has around 150,000 observations per year.[13] This means that if I were to use all the CZs I would only have around 70 observations per CZ on average. Moreover, since I distinguish between high- and low-skilled workers I would end up with geographic units of around 35 observations. Given the variance in wages in the US, this is not a feasible geographic unit. This leaves me with states as natural candidates for a geographic disaggregation, which I use throughout the paper.

2.5 Labor Market Outcome Variables

I use CPS data to compute three measures of wage: the weekly individual wage, the weekly average wage at the state level and the composition adjusted weekly wage in a state. All wages are in real 1999 dollars. The weekly wage is constructed from the yearly wage and the number of weeks worked in a year for every individual in the CPS sample.[14]

[13] This number includes all individuals irrespective of age. Around 60,000 observations can be used to compute wages.

[14] The CPS also provides the real hourly wage. This is the reported hourly wage the week previous to the week of the interview, in March of every year. I do not report results using this variable in the paper, but all the results are unchanged when using this real hourly wage instead of the real weekly wage. I use the weekly wage because there are more observations available. The wage and the number of weeks worked reported in a given year refer to the previous year. Thus, I will use the answers in 1996 to know the wage in 1995. An alternative to the March CPS data is the CPS Merged Outgoing Rotation Group

From individual-level information on wages I construct the two aggregate measures of the low-skilled wage for each state and each year. The first, which is the one I use primarily, is simply the average (log) wage of the full-time working population, excluding Hispanics from the computation[15]. For the second, used mainly in the Appendix, I follow the literature by running first stage Mincerian regressions to control for compositional effects and I use the state fixed effects as this aggregate measure of wages. In particular I run the following regression:[16]

$$lnwage_i = X_i * \beta_t + \delta_{t,s} + \varepsilon_i, \forall t \in [1992, 1998]$$

where $i \in I_L$ indicates individuals in the set of low-skilled workers and $s \in S$ indicates US states. The subscript t indicates that I run each year in a separate regression. Low-skilled workers are defined as high school drop outs and high school graduates. X_i are the standard controls (Card, 1999): potential experience, experience squared, a dummy for black, a dummy for females, a dummy for rural and a dummy for other races. I also include a dummy for Hispanic origin. $\delta_{t,s}$ is a set of fixed effects capturing the premium in different states. By just using the fixed effects this measure considers the wage of workers with no experience evaluated at the omitted dummy variables, i.e., white metropolitan male workers.

When I evaluate the impact of Hurricane Katrina I use the very same variables, using the American Community Survey (ACS) data instead of CPS. The main difference between the two data sets is the sample size. While the CPS has around 150,000 observations per year, the ACS has over 1 million individual observations before 2005 and over 3 million in more recent years.

I also use the CPS and ACS data to compute other labor market outcome variables. In particular I construct the unemployment share as the number of unemployed divided by the working age population. I prefer this measure over the more conventional unemployed over active labor market participants to limit the extent of the endogenous adjustment of labor market participation to the labor supply shocks I am studying. It also helps to limit the impact of the reforms of CPS questioning in 1994. The main results are not sensitive to this choice. I also use information in the CPS to compute the school enrolment rate, i.e., the number of individuals who report that they are attending a school divided by the population between 18 and 25 years old.

Finally I use CPS data to count employment levels and reallocation. For employment levels I simply compute the number of individuals who are in full time employment. For reallocation, I compute the share of low-skilled individuals either including or excluding the Hispanic workers to see its evolution in high- and low-immigration states. I also compute the internal in-migration and out-migration rates by computing the share of workers in a given location who report having lived in a different state in the previous year. I compute these distinguishing skill levels and age groups, depending on the application. This distinguishes the two possible mechanisms through which reallocation can take place: changes in the inflow to or the outflow from particular states. Unfortunately this information is not available for 1995, so the pre-shock

files. In the Appendix I report estimates using these alternative data.

[15]Ideally I would have preferred to exclude Mexicans or Mexicans and other foreign born people. As mentioned before, this information is only available after 1994, limiting the pre-shock series. I preferred to extend the pre-shock series at the cost of using the Hispanic origin variable to exclude former immigrants from wage and reallocation computations. The results do not change if instead I limit the analysis to post-1994 and I explicitly use the birth place as the variable distinguishing immigrants and natives.

[16]I follow Acemoglu and Autor (2011) and I only consider full-time, full-year workers. They are defined as workers who have worked at least 35 hours and 40 weeks a year and report a valid income wage. I further drop self employed workers and workers above and bellow 65 or below 18 years old. I also correct for top coding following the literature. Histograms of the raw data are available upon request; in particular histograms of raw weekly wage, experience levels and age. See also Autor and Katz (1999) or Katz and Murphy (1992).

period does not include this year when using in and out internal migration rates.

2.6 Summary Statistics

Table 2 shows the main variables used for the estimation of the causal effect of Mexican inflows on low-skilled native wages. They are divided into four blocks. The first block describes the various measures of net inflows at the state level, both in absolute and relative terms. While Mexican inflows were negligible in many states, there are a few that received large numbers of new workers every year. The largest inflow is in California, which in 1995 received slightly more than 300,000 (potential) workers, which represents almost 9 percent of the state's low-skilled labor force. This is around 50 percent higher than in a normal year of the 1990s.

Table 2: Summary statistics

Variable	Mean	Std. Dev.	N
Mexican inflows at state level			
Mexican Inflows (own estimates)	8,671.9	37,896.0	357
Mexican Inflows (Passel et al. (2012) estimates)	9,327.7	40,375.7	357
Mexican Inflows (INS+DHS)	7,215.3	31,555.8	357
Maximum number of Mexican Inflows (in a state)	326,305.7		
Relative Mexican Inflows (own estimates)	0.005	0.012	357
Relative Mexican Inflows (Passel et al. (2012) estimates)	0.006	0.013	357
Relative Mexican Inflows (INS+DHS)	0.004	0.01	357
Maximum number of Relative Mexican Inflows (in a state)	0.088		
Share of Mexicans (1994 onwards)	0.03	0.056	255
Labor Market Outcomes			
Average low-skilled wage	5.953	0.099	357
Average low-skilled wage (Mincerian regressions)	5.687	0.09	357
Average high-skilled wage	6.341	0.143	357
Unemployment rate	0.057	0.018	357
(log) state GDP	11.359	1.033	357
School Enrollment rate (25 years old)	0.415	0.067	357
GDP and exports			
US GDP growth rate	0.056	0.006	7
Mexican GDP growth rate	0.045	0.041	7
State Exports (in millions)	1,079.3	3,828.7	357
State GDP (in millions)	288,375.1	349,363.9	357
Ratio Exports to GDP at state level	0.002	0.003	357
Various variables, Katrina			
Relative Inflow from LA and MS	0.001	0.002	441
Average low-skilled wage	5.836	0.095	441
Unemployment rate	0.074	0.021	441
Internal in-migration rate (low-skilled)	0.031	0.013	441
(log) state GDP	11.959	1.041	441

Notes: These are the main variables used in the analysis of the causal effect of immigration on wages. The averages are unweighted, so do not necessarily coincide with the true US average. This data covers years the 1992-1998 and 2003-2011.

The second block describes labor market outcomes. Average wages of low-skilled workers at the state level are significantly lower than those of high-skilled workers. There is some dispersion across states, as one would expect given the various shocks that hit the economy and given the potentially different amenity levels in each state. Average wages do not differ significantly from the wages obtained from a first stage Mincerian regression, as can also be seen in this second block of summary statistics.

The third block provides some descriptive statistics on GDP and trade. It shows that trade usually makes up a very small fraction of the state GDP. In the case of California, the state receiving the largest amount of immigrants, the ratio of US exports to Mexico relative to state GDP is below .7 percent throughout the decade. Other states like Texas, Michigan, Arizona, Alabama, Louisiana, South Carolina and Delaware have higher or very similar ratios of exports to Mexico to GDP. In other words, Mexican immigration is substantially more important for California than exports to Mexico.

The final block provides some key variables for the exercise on Katrina. It shows how labor inflows from Louisiana and Mississippi are, in general, very low. The mean across US states is less than .1 percent of the state population. The relatively high variance of this variable reflects the Katrina shock.

3 Short-run effects of immigration

In this section I investigate the short-run effects of immigration on labor market outcomes. The usual empirical model to study these is to explain labor market variables of interest by the inflows of immigrant workers into these various labor markets relative to the local labor force (Borjas, 2003):

$$Y_{st} = \alpha + \beta * \frac{\text{Labor Inflow}_{st}}{\mathrm{N}_{st}} + X_{st} * \gamma + \delta_t + \delta_s + \varepsilon_{st} \tag{1}$$

where Y_{st} is our labor market outcome of interest, s are states or more generally regions, t is time, N_{st} is the size of the local labor force, X_{st} are time-varying state controls, and δ indicates the possible inclusion of fixed effects.

The concern with these regressions is that Mexican workers might be deciding where and when to migrate given the local labor market conditions of interest. We thus need an instrument with which to learn about the causal effect of immigration on labor market outcomes.

3.1 Instrument

As noted before in Figure 4 more Mexicans than usual moved to the US in 1995, while fewer returned to Mexico in 1995-97. Similarly, more workers moved out from Louisiana or Mississippi in 2005 and 2006. These will be the basis of the instrument. A simple way to capture this shock is to instrument the relative net inflows of Mexicans by the interaction of the year of the shock dummies and the share of Mexicans in each state in 1980. Specifically I define:

$$Z_{st} = \delta_t * \frac{Mex_{s1980}}{N_{s1980}}$$

where $\frac{Mex_{s1980}}{N_{s1980}}$ is simply the share of low-skilled Mexicans in each state in 1980 relative to the size of the low-skilled labor market in 1980. I use year dummies instead of a post shock dummy to account for the fact that the shock might have been of different intensity in different years.

My instruments are then Z_{st}. The main specification uses only 1995 as the year of the shock because I want to capture the very short-run effects. In the Appendix I show that the results are robust to using a number of alternative instruments[17]. In all cases, the identification comes from comparing states with themselves before and after the shock, given that the size of the shock was different in different states due to the uneven settlement pattern of the early immigrants.

When using Hurricane Katrina as the push factor I substitute the years 2005 and 2006 for the year 1995 and the stock of people from Louisiana and Mississippi in 2000, computed using Census 2000 data, for the

[17] I can use only the interaction of 1995 and the share of Mexicans in 1980, or the interaction of this share with year dummies for the period 1995 to 1997, the interaction of a dummy for the shock period and this share of Mexican or even the interaction of a post shock dummy and the share of Mexicans in 1980. All these alternatives are shown in the Appendix.

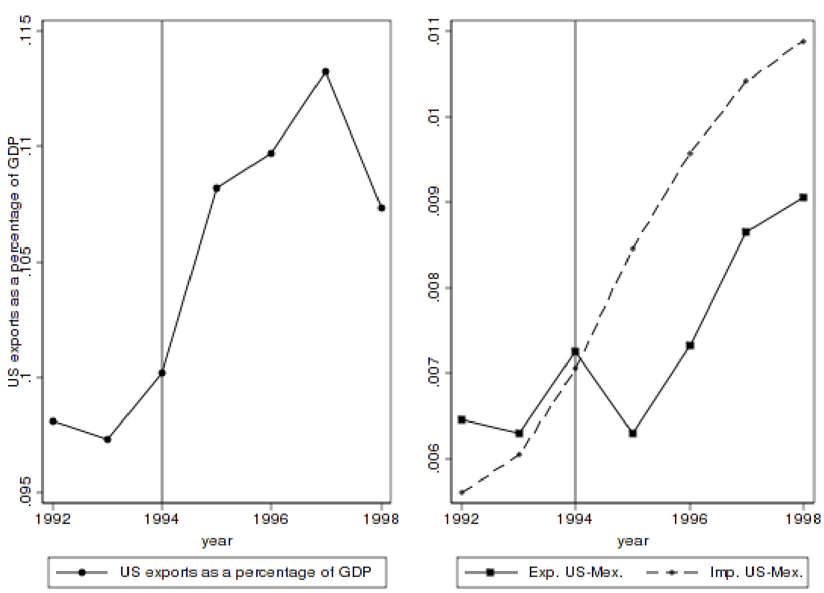
stock of Mexicans in 1980. Thus, my instrument for Katrina is the interaction of the year dummies for the shock period with the past outflows from Louisiana and Mississippi.

3.2 Exclusion Restriction

In any instrumental strategy one of the biggest concerns is that the exclusion restriction is violated. In this context it is possible that the Mexican crisis affected not only immigration but also US-Mexican trade relations.

More specifically, the devaluation of the Peso might have increased exports from Mexico to the US, relative to the trend. Figure 8 suggests that this was not the case. It also shows that exports from the US to Mexico in fact saw a significant decrease. If states exporting to Mexico are the same states where Mexican immigrants enter, then I might be confounding the effect of trade and immigration. Fortunately, even if there is some overlap, immigrants do not systematically enter states that export heavily to Mexico. The unconditional correlation between the relative immigration flows and the share of exports to Mexico (relative to state GDP) is below .5. Similarly, in an OLS regression with state and time fixed effects the covariance between these two variables is indistinguishable from 0.

Figure 8: US trade



Note: Exports US-Mex are exports from the US to Mexico divided by US GDP. Imports US-Mex are imports to the US from Mexico divided by US GDP. Total US exports are exports from the US to the rest of the world divided by US GDP. Mexican exports to the US did not increase above trend in 1995, while US exports to Mexico decreased in 1995, potentially affecting labor market outcomes. At the same time US exports to the rest of the world were slightly above trend in 1995. Source: Census Bureau (http://www.census.gov/foreign-trade/balance/c2010.html)

Furthermore, even if exports to Mexico and immigration from Mexico occur in the same states, it is harder to explain through trade why the negative effect is mainly concentrated on workers with similar characteristics to the Mexican inflows. I document the largest labor market impacts on young low-skilled workers in high-immigration states, some effects on older low-skilled workers and no effects on high-skilled workers, which matches the nature of the immigration shock.

To avoid the possible contamination of my estimates from the direct effect of trade on wages I include in some of my regressions (log) US states' exports to Mexico and (log) state GDP. This should control for the possible direct effect of trade on the US labor market[18].

3.3 Short-run effects of immigration on wages

In this section I estimate the causal effect of immigration on US local wages. I use the following equation for estimation:

$$\ln w_{st} = \alpha + \beta * \frac{\text{Labor Inflow}_{st}}{\text{N}_{st}} + X_{st} * \gamma + \delta_t + \delta_s + \varepsilon_{st} \tag{2}$$

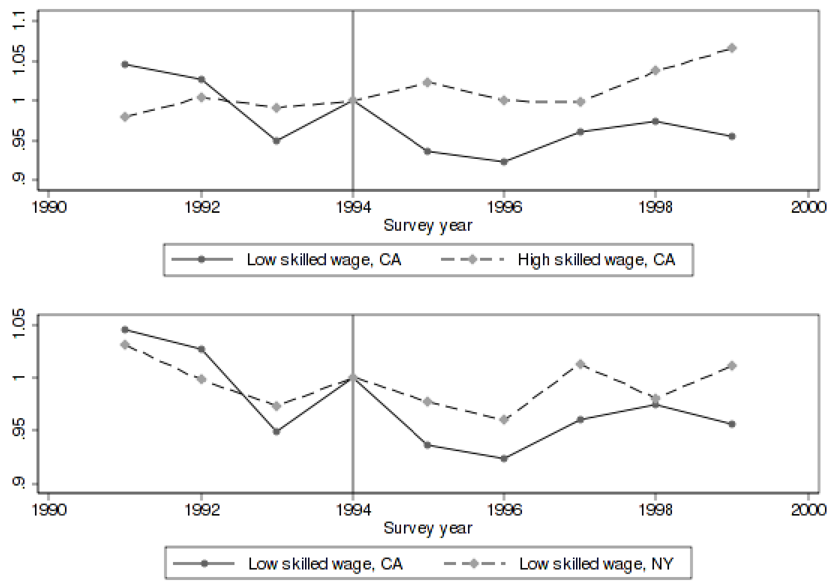
where, Labor Inflow $\in \{Mex_{st}, Kat_{st}\}$ is the flow of low-skilled Mexican or Katrina workers into state s at time t, while N_{st} is the population of native low-skilled workers. X_{st} is a vector of controls that includes the total population of low-skilled workers in a given state, the output of the state and its exports to Mexico. I also include state-specific time trends and state fixed effects. The total number of observations is 357: 50+1 states times 7 years [1992-1998] when using the Mexican shock. When using Katrina I have 441 observations: 49 states (all except for Louisiana and Mississippi) and 9 years of data.

A simple graphical representation shows the estimates I later report. Figure 9 shows the evolution of the average low and high-skilled wages in California and the evolution of low-skilled wages in a lower immigration state like New York. Wages are normalized to 1 in 1994 to make the comparisons simpler. A few things are worth noting from Figure 9. First, low-skilled wages decreased in 1993. In some states, unlike California, high-skilled wages also decreased in that year. This is probably a result of the economic downturn in 1992. Second, when comparing low and high-skilled wages in California we see that low-skilled wages clearly decreased in 1995 and 1996 and then recovered their pre-shock trend, while, if anything, high-skilled wages increased slightly in 1995. By the end of the decade high-skilled wages increased in California, probably showing the beginning of the dot com bubble. When instead we compare low-skilled wages in California and New York, we observe that the decrease in California is more pronounced than that of New York, where Mexican immigration was a lot less important.

The estimation exercise shows that the pattern I describe in Figure 9 is general. I could estimate equation 2 using OLS, but my estimates are likely to be biased. Mexican workers endogenously decide where to move within the US and workers already in the US are likely to arbitrage away differences in wages across locations. Moreover, amenity levels are likely to explain an important part of the variation in wages across states (Rosen, 1974), (Roback, 1982). The good weather in California is probably compensated through the permanently lower wages or higher housing prices of the Golden State which are unrelated to immigration. Thus, an essential first step towards estimating the causal effect of immigration or in-migrants on local labor wages is to include state fixed effects in the regression. This accounts for time invariant characteristics that may be correlated with immigration. A second necessary step is to include time fixed effects. These should account for any shocks that are common to the entire US. A third step is to include state specific time trends. This should account for the possibility that different states are on different growth paths. Ideally, we would like to compare states receiving an immigration shock with states in a similar pre-shock trend.

[18] Data for state exports to Mexico is provided by WISERTrade (www.wisertrade.org), based on the US Census Bureau. Exports are computed using "state of origin". "state of origin" is not defined as the state of manufacture, but rather as the state where the product began its journey to the port of export. It can also be the state of consolidation of shipments. Though imperfect, this is the best data available, to my knowledge, on international exports from US states.

Figure 9: Evolution of wages, raw data



Note: This figure reports the low-skilled average wage in California and New York and the high-skilled average wage in California. California is the highest immigration state, while New York is a good comparison state because it is comparable in economic terms but has lower levels of Mexican immigrants.

In fact, low-skilled wages were quite stable in the 1990s, as is documented in Acemoglu and Autor (2011), and trends were similar across states. If anything, as will become clearer later when discussing the longer run effects of immigration on wages, we observe that high-immigration states have a slightly negative trend, consistent with the longer run effects of immigration which I discuss later. This is also somewhat perceptible in Figure 9. This makes introducing fixed effects, state trends and controls my preferred specification.

Table 3 reports the results of estimating equation (2). Panel A shows the first stage regressions. They show that, during the shock, the supply of Mexican workers increased, especially in high-immigration states. Panel B shows the OLS regressions. Column 1 is just an OLS regression of wages on relative inflows. We see that the coefficient is not statistically different from 0. A number of reasons might account for this, from different amenity levels to the endogenous sorting of Mexicans within the US. Thus, these numbers are not very informative about the causal effect of immigration on wages. In Column 2, I include state and time fixed effects. We already observe that when making within-state comparisons, wages are lower when inflows are larger. In column 3 I incorporate GDP, exports and employment levels as controls, while in column 4 I include state-specific time trends. The estimates from these OLS regressions suggest that a 1 percent increase in the supply of low skilled workers reduces wages by around 1 percent. In Panel C I compare the years of the shock with the years that do not experience the shock. These are the IV regressions. In column 2 I only include state and time fixed effects; in column 3 I add to those the employment levels and state exports and GDPs as controls; and in column 4 I also include state specific time trends. In this Table I use only 1995 as the exogenous shock period. Columns (5)-(8) repeat the same exercise but using the wages of high skilled workers as dependent variable. Panel D shows the same exercise but using a first difference specification. In the Appendix I use other specifications, including 1996 and 1997 as the shock periods and limiting my time

Table 3: The causal effect of a local labor supply shock on wages

Mexican Shock

Panel A: First Stage

Dep. Variable: Relative Mexican Inflow	(1)	(2)	(3)	(4)
shock x share 1980	1.173***	0.381***	0.379***	0.373***
	0.135	0.069	0.069	0.067
State and time FE	no	yes	yes	yes
Controls	no	no	yes	yes
State trends	no	no	no	yes

Panel B: OLS Regressions

Dep. Variable: Average Weekly Wage	Low Skilled				High Skilled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mexican Inflow	0.405*	-1.135*	-1.061*	-0.896*	1.616***	0.037	0.243	0.539
	0.243	0.632	0.632	0.498	0.231	0.652	0.638	0.439
State and time FE	no	yes	yes	yes	no	yes	yes	yes
Controls	no	no	yes	yes	no	no	yes	yes
State trends	no	no	no	yes	no	no	no	yes

Panel C: IV Regressions

Dep. Variable: Average Weekly Wage	Low Skilled				High Skilled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mexican Inflow	-0.181	-1.222**	-1.189**	-1.419***	0.970	0.155	0.455	0.398
	0.465	0.578	0.588	0.516	0.668	0.859	0.812	0.771
F-stat First Stage	76.056	30.749	30.493	30.997	76.056	30.749	30.493	30.997
State and time FE	no	yes	yes	yes	no	yes	yes	yes
Controls	no	no	yes	yes	no	no	yes	yes
State trends	no	no	no	yes	no	no	no	yes

Panel D: IV Regressions, First Differences

Dep. Variable: Δ Average Weekly Wage	Low Skilled				High Skilled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Mexican Inflow		-2.009**	-1.607**	-1.501**		0.323	0.319	0.419
		0.797	0.716	0.731		0.698	0.695	0.665
F-stat First Stage		78.674	30.875	31.051		78.674	30.875	31.051
Time FE		yes	yes	yes		yes	yes	yes
Controls		no	yes	yes		no	yes	yes
State FE		no	no	yes		no	no	yes

Notes: $N_{mex} = 357$. "shock" is a dummy for the year 1995. "shock share 1980" is the interaction between the shock variable and the share of Mexicans by state in 1980. The IV specification is as discussed in the text. It is an interaction of a dummy for 1995 and the share of Mexicans in 1980. For the Mexican regressions, I obtain the same results when using the interaction of a dummy for 1995, 1996 and 1997 with the share of Mexicans in 1980. Panel regressions are at the state level between the years 1991-1999. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. "Mexican Inflow" is the relative inflow of Mexicans to low-skilled natives using my own estimates (see text for more details). Wages are average (log) state weekly wages. Regressions are weighted by the number of observations in the state and robust standard errors are reported. Controls include: GDP, exports to Mexico, employment levels.

period to 1992-1995 to exclude post-shock periods, while still being able to control for different state trends. Also in the Appendix, I show similar regressions using alternative measures of Mexican inflows, alternative measures of wages (controlling for observable characteristics), using first differences with various post-shock period lengths and excluding California or Texas from the regressions. I also report estimates using wage data from the CPS Outgoing Rotation groups, comparing high- and low-immigration states, playing with alternative definitions of my treatment and control groups.[19] Estimates from these alternative specifications range from -.7 to -2.[20] In columns (5)-(8) of Table 3 I report the results for high-skilled average wages. As expected, this coefficient is essentially 0, suggesting that the Mexican shock only affected low-skilled workers. Thus, all these estimates suggest that:

A 1 percent immigration-induced supply shock reduces wages by between 1 to 1.5 percent on impact.

In Table 4 I report the estimates of the effect of immigration on the average wage for younger and older workers.[21] It shows that the effect of immigration on wages is, if anything, higher for low-skilled native young workers than for older ones, though these estimates are less precise. This coincides with the nature of the Mexican immigrant shock, since fewer Mexicans of all ages returned to Mexico and more young low-skilled Mexicans moved to the US after the Peso Crisis hit. This will be a lot more salient when discussing unemployment shares.

Table 4: The causal effect of Mexican on wages by age group

	Mexican Shock						
	young low-skilled wage						
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	IV (5)	IV (6)	IV (7)
Mexican Inflow	0.574**	-1.054	-1.009	-0.917	-1.304	-1.344	-1.475*
	0.254	0.659	0.691	0.616	0.848	0.879	0.873
N	357	357	357	357	357	357	357
F-stat					30.749	30.493	30.997
State and time FE	no	yes	yes	yes	yes	yes	yes
Controls	no	no	yes	yes	no	yes	yes
State trends	no	no	no	yes	no	no	yes
	Mexican Shock						
	old low-skilled wage						
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	IV (5)	IV (6)	IV (7)
Mexican Inflow	0.589**	-0.993	-0.842	-0.649	-0.916	-0.825	-1.221**
	0.254	0.761	0.751	0.554	0.689	0.679	0.587
N	357	357	357	357	357	357	357
F-stat					30.749	30.493	30.997
State and time FE	no	yes	yes	yes	yes	yes	yes
Controls	no	no	yes	yes	no	yes	yes
State trends	no	no	no	yes	no	no	yes

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995. Panel regressions at the state level between the years 1991-1999. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Robust standard errors are reported. Controls include: GDP of state, exports of state to Mexico, levels of low-skilled young and old workers.

[19] The highest immigration states are CA, TX and AZ. In some cases I also include IL and NM as high-immigration states. In the Appendix I do various exercises comparing different sets of states and excluding CA or TX.

[20] All these estimates are significant at least at a 10 percent significance level independently if I use conventional standard errors, robust standard errors or standard errors clustered at the state level.

[21] Younger workers are below 35 years old.

3.4 Substitutability between immigrants and natives and between high school drop-outs and high school graduates

The estimation exercise presented so far rests on three key assumptions. First, I am implicitly assuming that natives and immigrants are perfect substitutes. This means that the inflow of Mexicans directly affects native wages. Second, I am also assuming that all the low-skilled workers, i.e., high school graduates and high school drop-outs are perfect substitutes too. Finally, I am assuming that my counts (and other sources' counts) of undocumented immigrants are accurate. I can directly test the first two assumptions, while I use the Katrina experiment, in the next subsection, to think about the third assumption.

To test whether Mexican workers and natives or high school drop-outs and high school graduates are perfect substitutes or not, I use two simple equations:

$$\ln wage_{it} = \delta_s + \delta_t + \alpha Hispanic_{it} + \beta Hispanic_{it} * Shock_t + Controls + \varepsilon_{ist}$$

$$\ln wage_{it} = \delta_s + \delta_t + \alpha HSDO_{it} + \beta HSDO_{it} * Shock_t + Controls + \varepsilon_{ist}$$

where $Hispanic$ is a dummy variable that takes value 1 if individual i is of Hispanic origin and 0 otherwise, $HSDO$ is a dummy indicating whether worker i is a high school drop-out and $Shock_t$ is a dummy variable that takes value 1 during the shock years, i.e., 1995-1997. The results of running this regression are shown in Table 5. The coefficient of interest is β. If β were negative it would mean that the shock affected Hispanic or high school drop-outs disproportionately more. This is what we would expect if Hispanic workers and Mexicans were closer substitutes than Mexicans and non-Hispanic workers or if high school drop-outs and high school graduates were imperfect substitutes. As can be seen in the different specifications in Table 5 this is not the case. β is always 0.

In the first three columns I limit the regression to the three highest immigration states[22], progressively including individual characteristics controls and state FE. We see that in these states, real wages decreased during the time of the shock. This is the effect of immigration, in first differences, identified before. We also observe that both Hispanic workers and high school drop-outs earn substantially less. However, Table 5 makes clear that they are not affected by the shock differentially. Column 4 in Table 5 shows the same regression without limiting the sample to high-immigration states. If reallocation were sufficiently fast, the effects would perhaps have been felt in the entire country and not so much in high-immigration states alone. This is not the case. Finally, I include all states in the country but I limit my sample to younger workers, since they tend to be more mobile and are the ones receiving a larger shock at the national level. Again, we do not observe a differential effect on Hispanic or high school drop-outs, suggesting that my assumption of perfect substitution was adequate. As mentioned before these two elasticities are key to knowing how many workers are absorbing the immigration shock in the US. As emphasized in Card (2009) and Ottaviano and Peri (2012), high school drop-outs and high school graduates form together a much larger pool of workers (more than 50 percent of the US labor force) than high school drop-outs. If these two groups are homogeneous then, the immigration of Mexicans -who are mainly high school drop-outs- spreads among many more natives. Similarly, whether natives and immigrants are perfect substitutes or not is key to understanding whether it is mainly former immigrants who suffer the labor market consequences of new

[22] CA, TX and AZ are the three states where Mexican immigrants represent a higher share of their low-skilled population.

Table 5: Substitutability between immigrants and natives and between high school drop-outs and high school graduates

	Mexican Shock				
	low-skilled Wage				
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
shock	-0.021	-0.017	-0.027**	0.004	-0.023*
	0.027	0.007	0.006	0.006	0.013
Hispanic	-0.275***	-0.363***	-0.378***	-0.378***	-0.182***
	0.027	0.017	0.010	0.012	0.019
shock x Hispanic	-0.007	0.004	0.011	-0.008	0.027
	0.012	0.010	0.009	0.014	0.026
r2	0.027	0.087	0.090	0.101	0.045
N	23492	23492	23492	147206	29513
	Mexican Shock				
	low-skilled Wage				
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
shock	-0.024	-0.014	-0.022*	0.007	-0.024*
	0.014	0.007	0.007	0.005	0.014
Drop-outs	-0.359***	-0.406***	-0.406***	-0.357***	-0.493***
	0.013	0.019	0.018	0.011	0.034
Drop-outs x shock	-0.004	-0.004	-0.003	-0.010	0.011
	0.030	0.023	0.023	0.010	0.034
r2	0.054	0.112	0.113	0.129	0.104
N	23492	23492	23492	147206	29513
Controls	no	yes	yes	yes	yes
State FE	no	no	yes	yes	yes
Sample	High-Immigration States			Full	Young
N	23492	23492	23492	147206	29513

Note: Shock is a dummy for the years 1995, 1996 and 1997. Weekly Wages are computed from CPS. Robust standard errors clustered at the state level. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Only low-skilled workers are included in the regressions. This table looks at whether Hispanic and non-Hispanic workers are perfect substitutes and whether high school drop-outs and high school graduates are perfect substitutes or not.

waves of immigration or whether natives also experience some effects. Like Card (2009) and Ottaviano and Peri (2012) but contrary to Borjas (2003) my results suggest that high school drop-outs and high school graduates are perfect substitutes. Unlike Card (2009) and Ottaviano and Peri (2012), these results suggest that, at least for low-skilled workers, natives and immigrants are indeed perfect substitutes.

3.5 Hurricane Katrina as an alternative natural experiment

The fact that Mexican and native low-skilled workers are perfect substitutes also means that I can use the Katrina experiment to see if the current estimates of Mexican inflows are accurate. Given that the shocks are similar, namely, an unexpected inflow of low-skilled workers into some US states, we would expect similar wage effects. This is shown in Table 6. The estimates from this alternative exercise are similar in magnitude to the Mexican shock. If anything, they tend to be larger, perhaps reflecting the direct effect of Katrina on states neighboring Louisiana and Mississippi or the lower productivity of Mexican low-skilled workers.

It is worth noting that the wage effects are only concentrated on low-skilled workers, like in the Mexican case. High-skilled workers' wages were not affected by the inflow of low-skilled workers, as shown in columns (5)-(8) of Table 6.[23]

[23] I do not show the equivalent of panel A of Table 3 because the small outflows from Louisiana and Mississippi –used in the instrument – makes the first stage be very small (yet significantly different than 0) numbers.

Table 6: The causal effect of a local labor supply shock on wages

	Katrina Shock			
	Panel A: First Stage			
	Dep. Variable: Relative Katrina Workers Inflow			
	(1)	(2)	(3)	(4)
shock x share 2000	0.186***	0.143***	0.139***	0.148***
	0.043	0.037	0.035	0.043
L.shock x share 2000	0.327***	0.283**	0.277**	0.282**
	0.097	0.118	0.117	0.128
State and time FE	no	yes	yes	yes
Controls	no	no	yes	yes
State trends	no	no	no	yes

	Panel B: OLS Regressions							
	Dep. Variable: Average Weekly Wage							
	Low Skilled				High Skilled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflow Katrina	-10.568***	-1.703***	-1.698***	-1.133	-13.008	-0.466	0.334	-0.010
	2.160	0.534	0.558	0.686	7.994	0.682	0.402	0.646
State and time FE	no	yes	yes	yes	no	yes	yes	yes
Controls	no	no	yes	yes	no	no	yes	yes
State trends	no	no	no	yes	no	no	no	yes

	Panel C: IV Regressions							
	Dep. Variable: Average Weekly Wage							
	Low Skilled				High Skilled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflow Katrina	-2.904	-1.815***	-1.749***	-1.957***	1.110	-0.501	-0.240	0.165
	2.909	0.615	0.648	0.430	4.315	1.066	1.317	0.767
F-Stat	10.307	10.515	12.090	7.406	10.307	10.515	12.090	7.406
State and time FE	no	yes	yes	yes	no	yes	yes	yes
Controls	no	no	yes	yes	no	no	yes	yes
State trends	no	no	no	yes	no	no	no	yes

Notes: $N_{kat} = 441$. The IV specification is as discussed in the text. It is an interaction of a dummy for 2005 and 2006 with the Louisiana and Mississippi worker shares in 2000. Panel regressions are at the state level between years 2003-2011. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Wages are average (log) state weekly wages. Regressions are weighted by the number of observations in the state and robust standard errors clustered at the state level are reported. Controls include: GDP, employment levels.

3.6 Unemployment shares

Though the main focus of the literature on immigration has been on wages, it is likely that immigration also affects other labor market outcomes. In this section I show that the immigrants from the Mexican Peso Crisis also had effects on low-skilled unemployment shares. As I argued before, the Mexicans that now moved into the US were not only low-skilled but also young. This is why younger low-skilled native workers were particularly affected by the unexpectedly large Mexican inflows. Older workers, even if they saw their real wages decrease because fewer low-skilled Mexicans returned to Mexico in 1995, were less affected in terms of unemployment shares. I show this in what follows.

To explore the effects of the Mexican shocks on unemployment shares I run the following regression:

$$\text{Unemployment Share}_{st} = \alpha + \beta * \text{Relative Mexican Inflow}_{st} + Controls_{st} + \varepsilon_{st} \tag{3}$$

where the unemployment share is computed as the share of native workers who are unemployed over the entire working age population and where the relative Mexican inflow is computed as before. To investigate whether younger or older workers are more affected, I compute the unemployment shares either using the entire population, only young workers or only old workers.

Table 7 shows the results of this regression. In the first column I report the simple OLS regression. In the cross state comparison, states with more immigrants seem to have higher unemployment shares. This is not very informative on the causal effect of immigration on unemployment shares, since other reasons could explain this, like favorable amenities in high-immigration states. As in previous tables, I introduce state and time fixed effects in column 2, controls in column 3 and state specific time trends in column 4. In columns 5, 6 and 7 I repeat the specifications 2,3 and 4 but instrumenting the inflow of immigrants as done in the previous tables. The estimates suggest that if Mexican inflows increase by 1pp then the unemployment rate increases by .2pp, though it is imprecisely estimated.

Table 7: The causal effect of Mexican inflows on unemployment shares

	Mexican Shock						
	Unemployment Share						
	OLS	OLS	OLS	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mexican Inflow	0.173***	0.137	0.091	0.147	0.186	0.192	0.211
	0.052	0.151	0.145	0.119	0.135	0.131	0.133
N	357	357	357	357	357	357	357
F-stat					30.749	30.493	30.997
State and time FE	no	yes	yes	yes	yes	yes	yes
Controls	no	no	yes	yes	no	yes	yes
State trends	no	no	no	yes	no	no	yes

Notes: The dependent variable is the unemployment share of low-skilled workers. All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995. Panel regressions at the state level between years 1991-1999. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Robust standard errors are reported. Controls include: GDP of state, exports of state to Mexico, levels of low-skilled young and old workers.

In Table 8 I show the same regression while distinguishing by younger and older workers. Like the wage regressions, the effects concentrate on younger workers. Indeed Table 8 shows that only young low-skilled workers were affected in 1995.

3.7 Reallocation of workers

How do these labor market effects translate into how labor reallocates across space? The most important critique of the cross-state or cross-city comparisons in the immigration literature is that workers relocate when hit by negative wage shocks (Borjas et al., 1996). This is what the spatial equilibrium literature would also suggest. The exogenous immigration shock of 1995 is unevenly distributed across US states, offering an opportunity to see how workers relocate from high-immigration states (HIS) to low-immigration states (LIS) when hit by an unexpected inflow of low skilled workers.

Figure 10 shows suggestive evidence that this is the case. It shows a plot of the evolution of the share of native low-skilled working age population in high- and low-immigration states. Several key points are worth emphasizing from this figure. First, the share of native low-skilled workers keeps decreasing over the decade. This reflects the well-known secular increase in education levels in the entire US which has been documented

Table 8: The causal effect of Mexican inflows on unemployment shares, by age

	Mexican Shock						
	Unemployment share young low-skilled workers						
	OLS	OLS	OLS	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mexican Inflow	0.089	0.306	0.256	0.261	0.745***	0.749***	0.738***
	0.061	0.255	0.258	0.249	0.252	0.255	0.259
N	357	357	357	357	357	357	357
F-stat					30.749	30.493	30.997
State and time FE	no	yes	yes	yes	yes	yes	yes
Controls	no	no	yes	yes	no	yes	yes
State trends	no	no	no	yes	no	no	yes
	Mexican Shock						
	Unemployment share old low-skilled workers						
	OLS	OLS	OLS	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mexican Inflow	0.160***	0.041	-0.011	0.070	-0.072	-0.082	-0.055
	0.053	0.147	0.130	0.113	0.137	0.128	0.131
N	357	357	357	357	357	357	357
F-stat					30.749	30.493	30.997
State and time FE	no	yes	yes	yes	yes	yes	yes
Controls	no	no	yes	yes	no	yes	yes
State trends	no	no	no	yes	no	no	yes

Notes: The dependent variable is the unemployment share of young and old low-skilled workers. All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995. Panel regressions at the state level between years 1991-1999. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Robust standard errors are reported. Controls include: GDP of state, exports of state to Mexico, levels of low-skilled young and old workers.

in the literature on skilled biased technological change, see Katz and Murphy (1992) or Acemoglu and Autor (2011).

Second, the share of native low-skilled potential workers is *higher* in low-immigration states.[24] This is perhaps not surprising, but it has not been emphasized in other papers. It indicates that when there are immigrant low-skilled workers in the economy, natives tend to either migrate to other states or acquire more education.[25]

Third, in 1996 the share of native low-skilled potential workers fell less than usual in low-immigration states while it fell more in high-immigration states, suggesting that either some low-skilled natives moved from HIS to LIS or some high-skilled natives moved from LIS to HIS. Another way to describe it is that the gap between the two lines in figure 10 is highest right after the shock. This is precisely the effect of immigration on labor reallocation that I want to capture in my econometric exercise. Reassuringly, this labor market reallocation seems to have started with some lag.

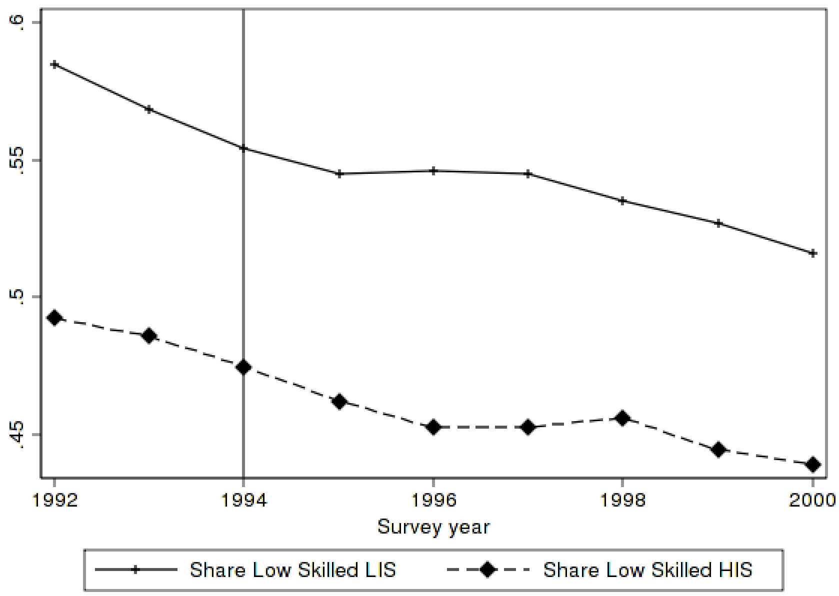
Fourth, given the fact that high immigration states received positive, persistent and large net inflows of Mexican low skilled workers and that the shares of native low skilled workers are parallel between high and low immigration states, as shown in Figure 10, indicates that high immigration states ended the decade with a higher share of total low-skilled workers. This is in line with the small long-run reallocation documented

[24] I use potential workers because I include all of the working age population to compute these shares. This includes individuals aged 18 to 65.

[25] In the Appendix I show that there is no clear evidence that more natives enrolled in school upon the arrival of Mexicans in 1995.

in Card (2007) and Card et al. (2008).[26] The reallocation I document in this paper is the response to the unexpected inflow of Mexicans in 1995, which can be seen in Figure 10 in the years 1996 and 1997. In other words, reallocation takes place as a response to wage changes.[27]

Figure 10: Share of native low-skilled potential workers in HIS vs LIS



Notes: This figure shows the share of native low-skilled potential workers in high-immigration states (HIS) and low-immigration states states (LIS). This is the number of low-skilled divided by the sum of low-skilled and high-skilled working age population. The vertical line indicates the time of the immigration shock. We observe that the share of low-skilled workers decreases in both high- and low-immigration states states, but that it decreases more after the shock, with some lag, in high-immigration states than in low-immigration ones.

The translation of Figure 10 into an equation is the following:

$$\text{Share of low-skilled Natives}_{st} = \alpha + \beta * \text{Relative Mexican Inflow}_{st} + Controls_{st} + \varepsilon_{st} \tag{4}$$

where the Share of low-skilled Natives at time t and state s is the number of low-skilled natives divided by the total amount of natives in the state (i.e. low and high-skilled). I exclude Hispanic workers to show that natives also respond to immigration inflows. The relative Mexican inflow is the same variable as in the wage equations. The controls include the levels of low-skilled and high-skilled workers and the (log) state GDP and state exports to Mexico.

An alternative specification to equation (4) is the following:

$$\text{Share of low-skilled}_{st} = \alpha + \beta * \text{Relative Mexican Inflow}_{st} + Controls_{st} + \varepsilon_{st} \tag{5}$$

where the share of low-skilled workers is computed using both natives and immigrants. I report this

[26] I have replicated the reallocation responses reported Card et al. (2008) between 1990 and 2000 and I obtain teh same results. They are available upon request.

[27] The leading explanation why wage trends are not responsive to long-run inflows of Mexicans relies on the technologies adopted in the different local labor markets. See Lewis (2012). This implies that normal inflows of immigrant workers alter the factor use in the local production function, but have small wage effects.

specification because it closely follows the literature (see Card and DiNardo (2000), Card (2005), Cortes (2008) or Peri and Sparber (2011)).[28] In this case, the inflow of low-skilled workers should increase one to one half the overall share of low-skilled workers in the first year and then decrease the subsequent year or years if there is some reallocation.[29]

Table 9 shows the results of estimating (4) and (5), in the upper and lower panel of the table respectively. The results of estimating equation (4) are in the upper part. In the first column we see that in general it is the case that high-immigration states have lower shares of native low-skilled workers in the cross-section. This is the gap between the two lines in Figure 10. To identify the causal effects of immigration on reallocation we need to look at within-state variation as before. In column 2 we see that by including state and time fixed effects we obtain a much smaller relationship between migration flows and the share of natives who are low-skilled in the population. Importantly, we obtain these results with the lagged inflow of Mexicans. If in a given year, like 1995, there is an especially high inflow of low-skilled Mexicans, in the following year, the share of low-skilled natives decreases. Columns 3 and 4 include controls and state specific time trends to the OLS regression. Estimates do not change substantially, suggesting that different states probably have similar trends that follow the national downward trend captured by the time fixed effects.

Table 9: The causal effect of Mexican on the share of low-skilled workers

	Share of native low-skilled workers						
	OLS	OLS	OLS	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.Mexican Inflow	-2.475***	-0.310**	-0.259**	-0.223*	-0.408**	-0.363*	-0.419**
	0.222	0.120	0.121	0.135	0.186	0.187	0.176
L2.Mexican Inflow		-0.028	-0.123	-0.373	-0.299	-0.361*	-0.476*
		0.198	0.191	0.369	0.236	0.207	0.256
N	357	357	357	357	357	357	357
F-stat					53.497	39.696	15.461
	Share of low-skilled (entire population)						
	OLS	OLS	OLS	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mexican Inflow	-0.153	-0.045	0.034	0.059	0.792***	0.879***	0.724***
	0.242	0.340	0.336	0.285	0.258	0.261	0.247
L.Mexican Inflow	-0.668***	0.128	0.088	-0.797**	-0.395	-0.399	-0.730**
	0.233	0.265	0.267	0.378	0.289	0.265	0.323
N	357	357	357	357	357	357	357
F-stat					58.005	52.282	14.924
State and time FE	no	yes	yes	yes	yes	yes	yes
Controls	no	no	yes	yes	no	yes	yes
State trends	no	no	no	yes	no	no	yes

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995. Lagged variables are instrumented by the lagged instrument. Panel regressions at the state level between years 1991-1999. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Robust standard errors are reported. Controls include: GDP of state, exports of state to Mexico, levels of low-skilled young and old workers. 'L.' denotes lagged variable.

Columns 5, 6 and 7 show the same specification as 2, 3 and 4 but using the instrument introduced before. Again, results are fairly similar across specifications. Quantitatively, they suggest that a percentage point increase in the low-skilled labor force due to Mexican workers leads to a .4 decrease in the share of native

[28] In the appendix I also show the regression: $\frac{\Delta L_{st}}{L_{s,t-1}} = \alpha + \beta * \frac{\text{Mex Inflow}_{st}}{L_{s,t-1}} + \varepsilon_{st}$ where L indicates the low-skilled labor force.

[29] It is one to one half because I use as explanatory variable the same as in the wage regressions. This is, I am computing the Mexican inflow relative to the low skilled population, which is around one half of the total population.

low-skilled workers in the following year and another .4 in the two years after the shock occurs. IV results suggest that OLS estimates are probably downward biased.[30]

The bottom part of Table 9 shows the results of estimating equation (5). In this case, we observe how, upon the new arrival of Mexican workers the share of low-skilled workers increases by more than one half, showing that the share of low skilled workers responds to the inflow of Mexicans and that the CPS may be undercounting Mexican slightly.[31] The following year, however, it decreases by almost as much as it increased. This brings the share of low-skilled workers in the local economies back to where it was. This is suggestive of interstate relocation in response to unexpected shocks.

The problem with Figure 10 and Table 9 is that they do not allow us to distinguish between the inflows and the outflows of workers to or from particular states, nor do they distinguish whether high or low-skilled workers are the ones relocating.[32] Unfortunately I can construct these for every year except 1995, because this is the only information available on the CPS.[33] To the extent that labor reallocation is taking place after 1995, this should not affect my estimates. Still the estimates from these regressions should be viewed slightly more cautiously, both because of the lack of data in 1995 and because the low migration rates in the US means there are few observations each year to compute them. The estimates on in migration and out migration rates that I obtain using the Mexico Peso Crisis are in line with evidence using the Katrina experiment, reported in the appendix, and with evidence in Monras (2013a) using the great recession of 2008.

To compute migration rates I use one of the questions in the CPS about the state of residence in the previous year. Using this question I can construct the number of people (high or low-skilled) that were living outside of state s at $t-1$ that at time t live in s, in other words the inflows to state s at time t. Similarly I can look at all the people that report that at time $t-1$ they were living in state s and that no longer live in state s at time t, in other words the outflows from state s at time t. By dividing by the current population (of a given skill level and age bracket) I can construct the migration rates. I can then use these measures to try to establish the effect of Mexican immigration on inflow and outflow rates.

More concretely, I can use the following equation:

$$\text{Migration rate}_{st} = \alpha + \beta * \text{Relative Mexican Inflow}_{st} + Controls_{st} + \varepsilon_{st} \tag{6}$$

where the migration rates indicate the in-migration rate or the out-migration rate depending on the specification. The migration rates can be computed using either the young low-skilled workers or the entire population, depending on the specification. Given that Mexican workers are especially affecting the labor market outcomes of young workers, this is where we should expect to find the native response. I include as controls the state GDP, the exports from the state to Mexico, as well as state and year fixed effects.

The results of running these regressions for younger workers are shown in Table 10: results for in-migration rates are shown in the upper part, while results for out-migration rates are shown below.[34] The first part

[30] These coefficients suggest substantial reallocation. This is, in part, driven by the fact that the explanatory variable includes all the Mexicans that arrived to the US in 1995, taking into account the possible undercount of illegal immigrants, as explained in the data section. In the Appendix I report the estimates using CPS data exclusively to show that the share of low skilled workers increases almost one for one with the inflow of low skilled Mexicans and then goes back to trend as observed also in Table 9. Relying only on CPS data to run the reallocation regressions has the drawback that I can only use post 1994 data.

[31] See the previous footnote and the Appendix.

[32] Borjas (2006) suggests that relocation is both through in and out migration rates. He does not look, though, at the response of migration to unexpected shocks as I do in this paper.

[33] The question on residence in previous year was not asked in the CPS in 1995.

[34] In these regressions I restrict the relative inflow of Mexican workers to younger workers too. This allows me to compare how many fewer young low-skilled workers move to high-immigration states for every Mexican young worker. If instead I use the inflow of Mexican workers relative to the low-skilled working force, the point estimates of the regression are .7 and the

of the Table shows OLS. Again, the first column shows that in the cross section in-migration rates are not related to Mexican immigration. In other words, it is not the case that in-migration rates are higher or lower in high-immigration states. When we include state fixed effects and state specific time trends we observe how this changes after the shock. Low-skilled workers that would have otherwise moved to high-immigration states seem to do less so after high inflows of Mexican workers.

Table 10: The causal effect of Mexican inflows on internal migration

	Mexican Shock							
	In-migration rates							
	young low-skilled workers							high-skilled
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.Mexican Inflow	-0.063**	-0.093	-0.093	-0.156**	-0.190**	-0.180**	-0.183**	0.131
	0.028	0.066	0.064	0.073	0.082	0.081	0.086	0.107
N	356	356	356	356	356	356	356	357
F-stat					25.829	25.983	26.575	26.636
State and time FE	no	yes	yes	yes	yes	yes	yes	yes
Controls	no	no	yes	yes	no	yes	yes	yes
State trends	no	no	no	yes	no	no	yes	yes
	Out-migration rates							
	young low-skilled workers							high-skilled
	OLS	OLS	OLS	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.Mexican Inflow	0.014	-0.053	-0.055	0.013	-0.101	-0.103	0.023	0.006
	0.031	0.069	0.069	0.074	0.108	0.112	0.101	0.130
N	342	342	342	342	342	342	342	350
F-stat					26.279	26.442	26.863	26.995
State and time FE	no	yes	yes	yes	yes	yes	yes	yes
Controls	no	no	yes	yes	no	yes	yes	yes
State trends	no	no	no	yes	no	no	yes	yes

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995. Lagged variables are instrumented by the lagged instrument. Panel regressions at the state level between years 1991-1999. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Robust standard errors are reported. Controls include: GDP of state, exports of state to Mexico, levels of low-skilled young and old workers. 'L.' denotes lagged variable.

In particular a one percentage point increase in the flow of young low-skilled workers leads to around a .2 percentage points decrease in the in-migration rate of native young low-skilled workers. By contrast, out-migration rates do not seem to respond instantaneously to the shock.

3.8 Comparing the short-run evidence from the Mexican Peso crisis and the Mariel Boatlift natural experiments

I have argued before that my results are consistent with much of the literature. The one study for which this is appears not to be true is Card's (1990) landmark study of the Mariel Boatlift. Card (1990) also looked at short-term effects of immigration inflows but, unlike this paper, found essentially no effects. What explains this difference? This section examines it in more detail.

In April 1980, Fidel Castro allowed Cubans willing to emigrate to do so from the port of Mariel. These Cubans – the "Marielitos" – were relatively low-skilled and some of them had allegedly been released from

significance increases, but it has a less clear interpretation.

prisons and mental hospitals by Cuban authorities (Card, 1990). As a result, around 125,000 Cubans migrated to the US between late April 1980 and October 1980. Slightly under half of them probably settled in Miami. Card (1990) uses this natural experiment to assess the effect of immigration on the labor market. Using a group of four comparison cities – Tampa, Houston, Atlanta and Los Angeles – Card (1990) reports no effect of Cuban immigrants on any group of the Miami labor force.[35] These findings are contrary to what is reported in this paper.

Two reasons could explain these differences. A first point is simply that although Card's point estimates are near zero, the standard errors are not small enough to rule out effects of the size I document in this paper. In addition, I show in the Appendix that his estimates are somewhat sensitive to the choice of data set. I am able to replicate Card's findings when using the CPS merged Outgoing Rotation files, but when using the alternative March CPS supplements I find that average wages of low skilled workers decreased by almost 8 percent while wages of high skilled workers increased by 4 percent. Both estimates are, however, imprecise. The results using the Mexican shock are not dependent on the data set I use, as can be seen in the Appendix.

Second and perhaps more importantly, as Card (1990) acknowledges, the nature of the "Marielitos" – who were perhaps not ready to enter the labor market immediately – and the particularities of Miami may, in part, explain why there is no evidence of a negative effect on wages. By contrast, Mexicans moving to the US in 1995 do not appear to be specially selected nor did they migrate to a singular local labor market, and therefore, their effects may be more representative of the effects of low skilled immigrants in the US.

4 Long-run effects of immigration

The fact that there is some relocation of low-skilled workers away from high-immigration states as a response to a negative shock to wages makes it more difficult to evaluate the longer run effects of immigration on labor market outcomes. There are a number of alternatives one can adopt. Empirically, I first show the evolution of low-skilled wage in high- relative to low-immigration states. I then show the wage changes over the decade of the 1990s in the different states and relate them to Mexican immigrant inflows. Finally, I abstract from locations and assume, as Borjas (2003) does, that different age cohorts suffer the shock differently. In this case, while both younger and older workers suffered from the immigration shock, we can compare whether workers entering the labor market in higher or lower immigration years have lower wages or not in 2000, relative to similar workers in 1990. A final alternative is to use the reported short-run estimates on the local labor demand elasticity and the sensitivity of native internal migration rates to local wages in a model built around these two key parameters. I can then calibrate the model and perform counterfactual exercises. I show the empirical strategies in the coming subsections, while I leave the discussion of the model for the last part of the paper.

4.1 Empirical investigation of the longer run effects on wages

4.1.1 Wage Dynamics

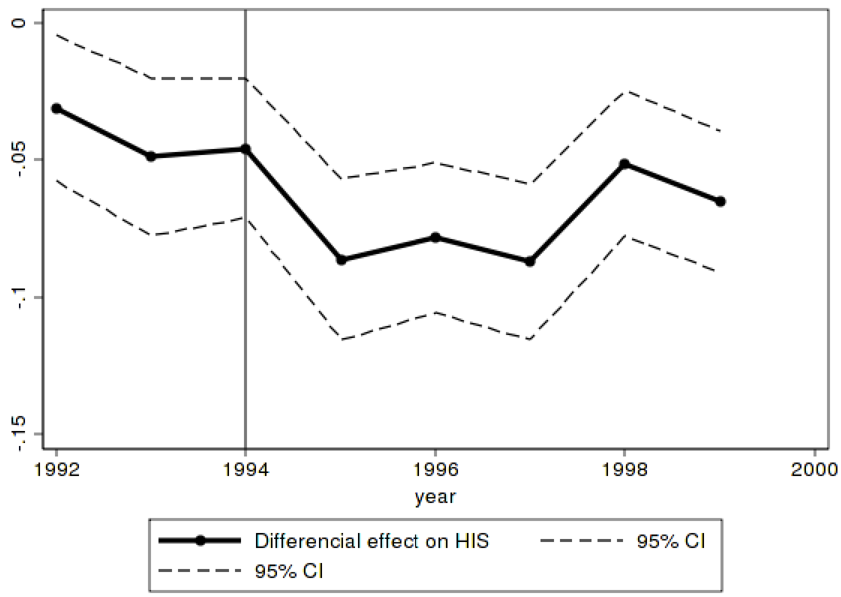
Figure 9, previously shown, suggests that wages recovered their pre-shock trends by 1998. We can generalize this figure by grouping the high-immigration states and running the following regression:

[35] Card distinguishes by racial groups and quartiles in the wage distribution.

$$\ln wage_{ist} = \delta_s + \delta_t + \sum_t \beta_t \delta_t HIS_s + Controls + \varepsilon_{ist}$$

where HIS_s indicates whether the state is a high-immigration state, δ_s are state fixed effects and δ_t are year fixed effects. Figure 11 plots the coefficients of the interaction of year fixed effects and the high-immigration state dummy, which is the differential effect of each year on wages of workers in high-immigration states:

Figure 11: Wage differential by year



Notes: This graph reports the coefficient of a regression of (log) weekly wages at the individual level on the interaction between year dummies and an indicator dummy for high-immigration states. 1991 is the omitted year. The regression does not allow for a different time trend between high- and low-immigration states.

The graph shows that in high-immigration states, wages of low-skilled workers were around .05 log points lower before 1994. In 1995, they were almost .1 log points lower and they continued at this level until 1997. In 1998 they returned to the original .05 log points. To some extent this Figure is very similar to the raw wages shown in Figure 9. It confirms, that, if anything, low-skilled wages may have a slightly decreasing trend in high-immigration states, something that may well be a consequence of immigration itself.[36]

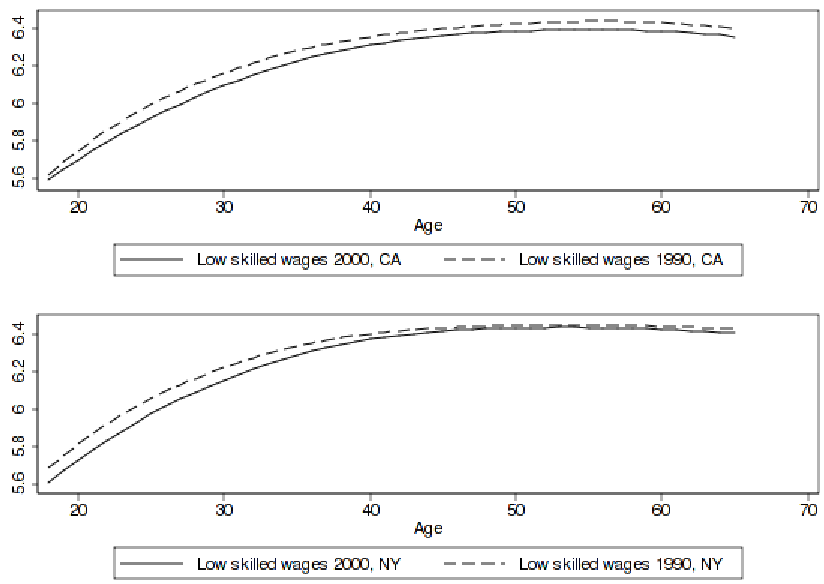
4.1.2 Long-run effect on wages in decennial data

Table 3 identifies the effect of immigration on wages from very short-run comparisons. The identification comes from the drop in wages of the specific group of workers, i.e., low-skilled, who are competing more closely with the Mexican arrivals. Figures 9 and 11 suggest that wages may have recovered in high-immigration states after the shock, at least to some extent. We can also see this by replicating some of the results in the literature, in particular Altonji and Card (1991).

[36]If I allow for a high-immigration specific trend then the only estimates that are distinguishable from 0 are the ones for 1995-1997.

Figure 12 shows the average weekly wage distribution of low-skilled workers in New York and California in 1990 and 2000. There are a few things worth noting. First, real wages of low-skilled workers decreased slightly during the 1990s. Second, they did more so for younger workers, something that coincides with the age of the Mexicans that migrated to the US during this period. Third, the wage of younger low-skilled workers did not decrease more in California (a high-immigration state) than in New York (where Mexican immigration is much less important). This is suggestive that Mexican inflows did not affect different states differently, but that they might have affected the wages of younger low-skilled workers disproportionately. Oreopoulos et al. (Forthcoming) suggest that labor market conditions of workers entering the labor force have lasting consequences. If this is true and there is substantial mobility of workers across space in response to wage changes, we should expect little or no effects of Mexican workers across local labor markets, but stronger wage effects for those low-skilled workers that experienced larger inflows of Mexicans when entering the labor force.

Figure 12: Low-skilled wages distribution in selected states



Notes: This figure shows the wage of native low-skilled workers by age for California and New York. The wage distributions have been smoothed using locally weighted scatterplot smoothing.

It is easy to translate the figure into a regression framework:

$$\ln(\text{wage}_{a,s,2000}) - \ln(\text{wage}_{a,s,1990}) = \alpha + \beta * \%\Delta \text{ in Lab. Force by Mex}_{a,s} + \delta_a + \delta_s + \varepsilon_{a,s} \tag{7}$$

where $\%\Delta$ in Lab. Force by $\text{Mex}_{a,s} = \frac{\text{Mexican Inflows in 90s}_{a,s}}{\text{Labor force in 1990}_{a,s}}$ is the labor supply shock induced by immigration, and $\ln(\text{wage}_{a,s,2000}) - \ln(\text{wage}_{a,s,1990})$ is the change in native average wages of cohort a in state s between 1990 and 2000. I limit this regression to low-skilled workers.

This specification is very similar to the ones used in Card (2001) or Altonji and Card (1991) and in Borjas (2003). Altonji and Card (1991) emphasize the spatial component, i.e., they assume that low-skilled workers of all ages are perfect substitutes and immobile, at least to some extent, across space. In terms of this regression, it means that they omit the age variation. Borjas (2003) instead assumes that workers are perfectly mobile and that workers are good substitutes only within their age cohorts. This is to say, he omits the variation in s.

To interpret the previous regression in a causal way we need to find good instruments. Mexicans might be selecting particular states to take advantage of good economic opportunities. Also, Mexicans of a particular age might be selecting specific states if the wages for their age group are particularly favorable or may decide not to migrate if their labor market prospects in the US are or become less favorable in particular states. This is why I instrument these regressions. As in previous literature, I use the geographic distribution in the previous decade (1980) to predict where the Mexicans will move to.

In the first two columns of the upper panel of Table 11 I show the spatial comparisons. Column 1 shows that a simple OLS regression of the change in wages in the immigration-induced labor supply change is likely to be biased. Mexicans are choosing what locations to move to and natives are likely to respond to Mexican inflows. Column 2 instruments using the migration network instrument. As found in the literature, this makes the coefficient slightly more negative and in this case, statistically different from 0. It suggests that states that received earlier and probably more persistent immigration shocks are the ones whose low-skilled wages decreased more. Instrumenting also increases substantially the amount of variation explained, suggesting that although most of the short-run wage effects previously estimated are dissipated across space, we are still able to find some traces in the cross state regressions. In other words, states that started with higher immigration levels have a slightly more negative trend in low-skilled wages.

Interestingly, the first two columns of the bottom part of Table 11 show a very different picture of the impact of Mexican migration on high-skilled wages. The IV specification suggests no causal effect of low-skilled immigration on high-skilled wages. The fact that with the OLS regression I obtain a positive and statistically significant coefficient probably means that new inflows of Mexicans moved towards states where the high-skilled wages were growing.

In the last two columns of Table 11 I show the age comparisons. Again, I restrict the upper part of the table to low-skilled workers and the bottom part to high-skilled ones. Given that the age distribution of Mexicans migrating to the US is fairly stable across years, we can use it together with the yearly aggregate inflows to predict what age groups suffered a larger immigration shock when entering the labor force. This can be used as an instrument for the share of Mexicans in each age group. This is the regression that Borjas (2003) stresses, and I obtain similar results, but in this case instrumented by an exogenous shock. The results of this exercise are shown in Columns 3 and 4 of Table 11. In Column 3 I report the simple OLS regression. The coefficient might again be biased because re-emigration rates or other labor market outcomes may readjust as a response to the migration shocks. In Column 4 we see the likely magnitude of this bias. These findings apply, as one would expect, only to low-skilled workers. High-skilled workers entering the labor force with high Mexican inflows did not see any effect on their wages.

The last part of Table 11 shows the first stage regression. We observe that the predicted inflows are a good predictor of the actual inflows as established in the literature. However, the coefficient in this first stage regression is smaller than in the literature. Two facts account for that. First, I have computed the Mexican inflows from the 2000 US census using the question previously discussed on when each Mexican moved to the US sccording to the 2000 US Census question because this reflects the actual choice of local labor market of the Mexicans in 2000. This is slightly different than what most of the literature does when simply comparing the Mexican stock in 1990 and 2000. Second, I have used an upper bound on the total Mexican inflows over the 90s to construct the predicted Mexican inflows.

Table 11: Long-run effect of Mexican immigration on low-skilled wages

	Cross-State		Cross-Age	
	low-skilled			
	Dep. Var: %Δ in Native wage between 1990-2000			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Mexican Inflow	-0.082	-0.187**	-0.446***	-0.525***
in the 1990s	0.092	0.083	0.033	0.054
F-stat		56.054		197.951
r2	0.058	0.359	0.256	0.248
	Cross-State		Cross-Age	
	high-skilled			
	Dep. Var: %Δ in Native wage between 1990-2000			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Mexican Inflow	0.169***	-0.083	0.086	-0.158
in the 1990s	0.060	0.067	0.134	0.155
F-stat		37.594		200.572
r2	0.212	0.157	0.004	-0.031
	First Stage			
	Dep. Variable: Mexican Inflow in the 1990s			
		OLS		OLS
	(1)	(2)	(3)	(4)
Predicted Mexican		0.338***		0.394***
Inflow		0.045		0.028
r2		0.830		0.795
N	51	51	48	48

Notes: This table shows the results of regressing the percentage change in native low-skilled weekly wage on the change in labor supply accounted for the Mexicans arriving in the US between 1990 and 2000. The IV for the cross-state comparisons is the immigration networks, while the IV for the cross-age comparisons is the interaction between the age distribution of immigrants and the aggregate yearly inflows in the 1990s. I use 48 age categories and 50+1 states. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Robust standard errors are reported. Regressions are weighted by the number of observations in the state or age category used to compute wages. The upper part reports the results of the Mexican induced change in the low-skilled labor force on low-skilled wages, while the bottom part shows the same low-skilled labor shock on high-skilled wages.

4.2 Model

While it is possible to evaluate the short-run effects using a clear natural experiment, spillovers across states due to labor reallocation makes it more difficult to evaluate longer run effects. In the short run, each local labor market, in this case states, is closed, so standard models of the aggregate labor market apply (see the canonical model discussed in Acemoglu and Autor (2011) or Katz and Murphy (1992)). In the longer run, internal migration flows link the various local labor markets, spreading local shocks to the rest of the economy. Standard models in the spatial economics literature in the spirit of Rosen (1974) and Roback (1982) are suited to analyzing the long run, once adjustment has taken place (see also Glaeser (2008), Moretti (2011) or Allen and Arkolakis (2013)). Fewer models in this literature are suited to study the transition dynamics.

Two seminal contributions introduced transition dynamics into a model with many regions: Blanchard and Katz (1992) and Topel (1986). For instance Blanchard and Katz (1992) report that wages seem to converge spatially after around 8 years, while unemployment rates converge faster. Their model has only one type of labor, but there is a downward sloping demand for labor in every region because regions do not necessarily produce the same goods. In the estimation of their model, they rely mainly on time series variation, although they also use Bartik (1991) type instruments like subsequent literature (see Diamond

(2013) and Notowidigdo (2013)). They do not microfound the migration decisions, something that these more recent papers do using discrete choice theory. Both Diamond (2013) and Notowidigdo (2013) have two skill types and reallocation costs, as in Topel (1986), but they model the reallocation decision using a discrete choice model.

The model I develop in this section is similar to the ones developed in the internal migration literature (see Molloy et al. (2011), Wozniak (2010) or Diamond (2013)) and the international migration literature (see Hanson and Grogger (2011) and Bertoli and Fernandez-Huertas (2012)).[37] However, I put higher emphasis on the transition dynamics, both on quantitatively assessing when we should expect spatial convergence (in wages) and how this relates to the short-run local labor demand elasticity and the sensitivity of internal migration to local labor market conditions, previously estimated.

The model has S regions representing US states. There is a single final consumption good that is freely traded across regions, at no cost. Workers, who can be high or low-skilled, are free to move across regions but each period only a fraction of them considers relocating.[38] They live for infinitely many periods. At each point in time they reside in a particular location s and need to decide whether to stay or move somewhere else. Once this decision is made they work and consume in that location. Workers are small relative to the labor market so they do not take into account the effect they have on the labor market when relocating. Also, they have idiosyncratic tastes for living in each specific location. This is the basis for the location choice that derives optimal location using discrete choice theory (see McFadden (1974) and Anderson et al. (1992)). In the paper, I assume that workers only look at current economic conditions to determine their location. In the Appendix I show that the implications are very similar to the case where workers are forward looking. The long-run equilibrium coincides with the equilibrium in standard spatial equilibrium models, where indirect utility is equalized across space. In contrast to more standard spatial equilibrium models, wages may be different across locations in the short run.

4.2.1 A simplified version of the model

To begin building the main intuitions of the model, I describe a graphical version of the 2 region case, to then generalize it to many regions and provide the analytical details. In this simple case, where there are only two locations, the model can be easily represented in a graph. I call these region 1 or high-immigration state (HIS) and region 2 or low-immigration states state (LIS). Region 2 is denoted by an asterisk.

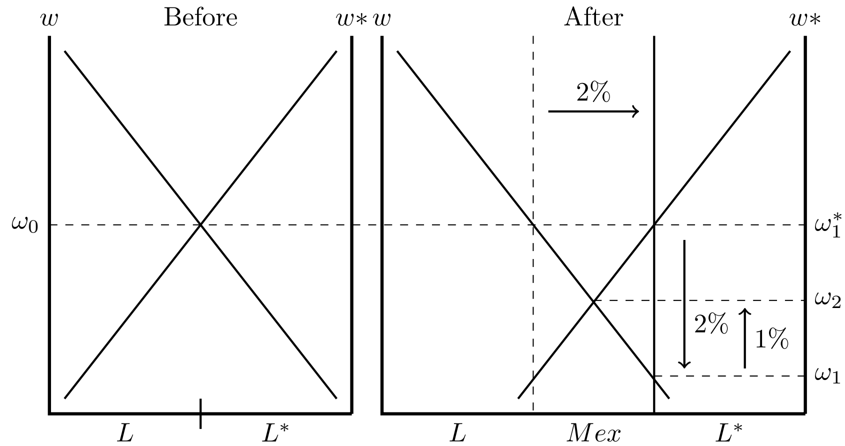
Figure 13 shows a simple graphical representation of this model. The right panel shows the equilibrium before immigrants arrive. In the left axis we have the wages in the first region, while the right axis denotes the wages in the second region. With two factors of production that are imperfectly mobile, the labor demand is downward sloping. With two regions the labor demand in one region is the labor supply in the other region, like in the specific factors model (see for example Borjas (1995)). Where these meet is the equilibrium wage in the national labor market, denoted by ω_0.[39] The horizontal axis determines how many people live in each of the two regions of this economy. Since the model has two factors of production, it is worth noting that I only represent one of the two labor markets. A similar graph applies to the labor market for high-skilled workers. The two markets are linked through the production function which in turn determines the shape

[37] Similar models have been used in the macroeconomics literature to investigate the reallocation of workers across sectors. See Artuç et al. (2010) or Pilossoph (2013).

[38] As written, the model abstracts from fixed factors (e.g., land) that can influence the scale of states in order to focus on incentives in light of disturbances to an initial equilibrium.

[39] Instead of using wages in the vertical axis I could have generalized by allowing amenities to be different across locations. To include amenities we only need to read ω as the wage multiplied by the local amenities.

Figure 13: Graphical representation of the model with 2 regions



Notes: This figure shows the model in the special case of two regions. The left panel shows the long-run equilibrium without migration. The right panel shows how the equilibrium changes when there is an inflow of immigrants.

and the position of the local demand curve. If the demand for high-skilled workers decreases in one location, so does the demand for low-skilled workers.

The right panel of Figure 13 shows the case of an exogenous increase in the number of low-skilled workers in region 1 of 2 percent of region's 1 population, or 1 percent of the national population. This is shown by the increase Mex in the x-axis. In the short run, factors are fixed, so wages absorb the shock. This creates a wedge between the low-skilled wages in regions 1 and 2, indicated by ω_1^* and ω_1 respectively. In the similar graph, but for high-skilled workers, the increase in low-skilled workers translates into higher demand for high-skilled workers, increasing their wage on impact.

Over the longer run workers move, equating the wage across locations. This is denoted in Figure 13 as ω_2. The figure also shows the magnitudes that I find in the two region symmetric case. In particular it shows that an increase in the labor supply in one region of 2 percent decreases wages by 2 percent. Over the long run, wages decrease by only 1 percent. A graphical representation of this adjustment is represented in Figure 14. In Figure 14 I have labelled time as months, but in the absence of a specific estimation this is an arbitrary choice.

In what follows I introduce the general version of this model.

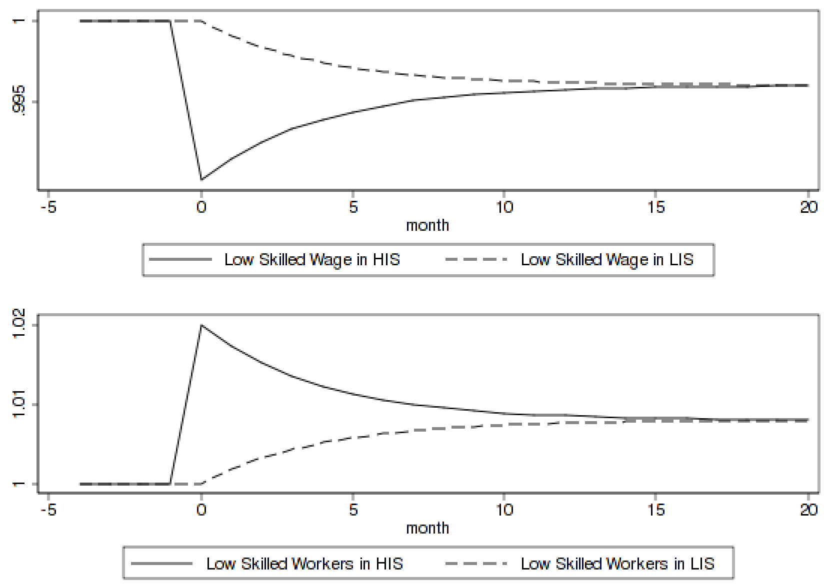
4.2.2 Utility Function

Workers derive utility from final good consumption, the amenities in a given location and the idiosyncratic valuation of the location:

$$U^i_{s,s'} = A_{s'} c^i_{s'} exp(\epsilon^i_{s'}) \tag{8}$$

where $A_{s'}$ denotes amenities (that depend on the skill level), $c^i_{s'}$ denotes consumption of individual i that lives in s at time t and moves to region s'. $\epsilon^i_{s'}$ is a random variable that represents individual idiosyncratic tastes when deciding where to live. A convenient assumption, as will become clear later on, is that amenities are proportional to the size of the local labor force. To save notation I do not explicitly label variables by t. Instead I indicate past variables with a -1 subscript. Only when it becomes unavoidable will I introduce

Figure 14: Path of adjustment to an unexpected labor supply shock



Notes: This figure shows the evolution of wages and employment in a two region world where high-immigration state (HIS) receives an unexpected immigration shock. Wages decrease on impact in HIS and slowly converge to wages in the low-immigration states state (LIS) as low-skilled labor relocates away from HIS.

the time subscript.

Workers earn the market wage of the location they reside in. Since there is only one good and no savings, they spend all of their wage on this good.

Indirect utility of workers is then given by the local wage for their skill type $\omega_{s'} \in \{w_{s'}, h_{s'}\}$, the amenities and the idiosyncratic draw they get for location s', given that they live in s:

$$lnV^i_{s,s'} = lnV_{s,s'} + \epsilon^i_{s'} = lnA_{s'} + ln\omega_{s'} + \epsilon^i_{s'} \tag{9}$$

Note that indirect utility has a common component to all workers $lnV_{s,s'}$ and an idiosyncratic component $\epsilon^i_{s'}$ specific to each worker. The variance of ϵ determines whether the common component or the idiosyncratic component has a higher weight in this decision.

4.2.3 Location Choice

Workers decide where they want to reside given the indirect utility they get in each place. This is, workers maximize:

$$max_{s' \in S}\{lnV_{s,s'} + \epsilon^i_{s'}\} \tag{10}$$

The general solution to this maximization problem gives the probability that an individual i residing in

s moves to s':

$$p^i_{s,s'} = p_{s,s'}(A_s, \omega_s, F; s \in S) \tag{11}$$

Only a fraction η of workers decide on relocation each period.[40] This parameter η is important for the calibration, since the model would otherwise over-predict yearly bilateral mobility in the absence of shocks. By the law of large numbers we can then use equation (11) to obtain the flow of people between s and s':

$$P_{s,s'} = \eta * p^i_{s,s'} * N_s \text{ for } s \neq s' \tag{12}$$

where N_s is the population residing in s. Note that this defines a matrix that represents the flows of people between any two locations in the economy.

4.2.4 Dynamics

In order to use equation (12) for estimation it is convenient to introduce some notation and some assumptions on the idiosyncratic tastes ϵ. By definition, the number of individuals of a certain skill at time t is the number of individuals who were living in that location (possibly times the natural growth rate n_s) plus those who arrive minus those who leave:

$$N_s = (1 + n_s)N_{s,-1} + I_s - O_s \tag{13}$$

Thus, internal relocation can take place through either in-migration or through out-migration. We can use the definition of the flow of people across locations to define the in and out-migration rates from any location in the economy:

$$\text{In-migration rate}_s = \frac{I_s}{N_s} = \frac{\sum_{k \neq s} P_{k,s}}{N_s} \tag{14}$$

$$\text{Out-migration rate}_s = \frac{O_s}{N_s} = \frac{\sum_{k \neq s} P_{s,k}}{N_s} \tag{15}$$

Obviously, the probability of moving from s to s' is increasing in wages in s', amenities in s' and decreasing in wages in s and amenities in s.

Like most of the literature I assume that ϵ is extreme value distributed.[41] This has the nice property that the difference in ϵ is also extreme value distributed and that this results in a closed form solution for the probability of an individual moving from s to s'. We can use this to write the bilateral flows as follows:

$$P_{s,s'} = \eta N_s \frac{V_{s,s'}^{1/\lambda}}{\sum_j V_{s,j}^{1/\lambda}} \tag{16}$$

where λ governs the variance of the error term. Lower values of λ, i.e., lower variance of the idiosyncratic error, makes people more sensitive to the local economic conditions and thus reallocation across local labor markets is faster.

[40] An alternative is to include fixed costs of moving. Doing so delivers similar qualitative results but introduces non-linearities that are difficult to handle and create non-desirable properties. I discuss this in the appendix.

[41] Moretti (2011) assumes instead a uniform distribution, the other one that admits close form solutions.

Under these assumptions one can prove (see Appendix) that the derivative of in-migration rates in s with respect to (log) wages in s is approximately $\frac{1}{\lambda}\frac{I_s}{N_s}$, while out-migration rates are generally less responsive. The intuition behind this result is the following. First, note that the most important thing for migration from s to s' is the wage in s'. Wages in s only enter by changing the denominator in (16). This means that when a negative shock affects wages in s it will have a strong influence on all the different flows of workers from any k region towards s, while it will have a relatively smaller effect on outflows from s. This makes in-migration rates more responsive than out-migration rates, particularly when shocks are concentrated in one or a small number of regions,[42] something I also documented in the empirical section. Furthermore, the estimate of a regression of internal in-migration rates on wages has a clear structural interpretation: we can recover the parameter λ from the estimate and the migration rate. This can be expressed more concisely as follows.

Proposition 1. *If ϵ_s^i are iid and follow a type I Extreme Value distribution with shape parameter λ then, in the environment defined by the model, we have that:*

1. $\partial(\frac{I_s}{N_s})/\partial \ln w_s \approx \frac{1}{\lambda}\frac{I_s}{N_s}$
2. $\partial(\frac{O_s}{N_s})/\partial \ln w_s > 0$, *but tends to 0 as the number of regions increases*

Proof. See Appendix. □

4.2.5 Production Function

The production function in all regions is the same: a perfectly competitive representative firm producing according to:

$$Q_s = B_s[\theta_s H_s^{\rho} + (1-\theta_s)L_s^{\rho}]^{1/\rho} \tag{17}$$

where L_s is low-skilled labor and H_s is high-skilled labor. θ_s represents the different weights that the two factors have in the production function, while ρ governs the elasticity of substitution between low- and high-skilled workers. B_s is Total Factor Productivity (TFP) in each state. We could also introduce factor augmenting technologies, as in Acemoglu and Autor (2011).[43]

4.2.6 Labor market

The marginal product of low-skilled workers is:

$$w_s = p_s(1-\theta_s)B_s^{\frac{\sigma-1}{\sigma}} Q_s^{\frac{1}{\sigma}} L_s^{\frac{-1}{\sigma}} \tag{18}$$

where $\sigma = 1/(1-\rho)$ is the elasticity of substitution between high- and low-skilled workers. This defines the labor demand curve.

Similarly, the marginal product of high-skilled workers is:

$$h_s = p_s\theta_s B_s^{\frac{\sigma-1}{\sigma}} Q_s^{\frac{1}{\sigma}} H_s^{\frac{-1}{\sigma}} \tag{19}$$

[42] See more details in the Appendix.

[43] None of the results that I will report below change if those technological levels are exogenous to immigration. On the contrary, if technology responds to immigration shocks, some of the results will change. As is common in the literature, I do not consider other factors of production like capital. As long as other factors enter the production function in a Hicks-neutral way this does not affect relative factor rewards. See also Card and Lewis (2007) and Lewis (2012).

We can normalize $p_s = 1$. Free trade will guarantee that prices are the same across regions.

4.2.7 Equilibrium

The definition of the equilibrium has two parts. I start by defining the equilibrium in the short run. It satisfies three conditions. First, given the amenity levels and wages in each location, workers maximize their utility and decide where to live. Second, firms take as given the productivity B_s, the productivity of each factor θ_s and factor prices in each location to maximize profits. Finally, labor markets clear in each location. This equates the supply and the demand for labor and determines the wage in every local labor market. More formally:

Definition I. *A short-run equilibrium is defined by the following decisions:*

- *Given* $\{A_s^l, A_s^h, w_s, h_s\}_{s\in S}$ *consumers maximize utility and location choice*
- *Given* $\{\theta_s, B_s, \sigma, w_s, h_s\}_{s\in S}$ *firms maximize profits*
- *Labor markets clear in each* $s \in S$ *so that* $\{w_s, h_s\}$ *are determined*

We can define the long-run equilibrium by adding another condition. In words, I say the economy is in long-run equilibrium when bilateral flows of people of every type are equalized between regions. More specifically,

Definition II. *Given* $\{\theta_s, B_s, \sigma, A_s^l, A_s^h\}_{s\in S}$ *fixed, a long-run equilibrium is defined as short-run equilibrium with equalized bilateral flows of population across locations. This is:*

$$P_{s,s'} = P_{s',s}, \forall s, s' \in S$$

for both high- and low-skilled workers.

4.2.8 Properties of the model

Only a share η of workers considers relocating each period. This implies that, depending on the size of local shock and the sensitivity of workers to local shock, reallocation may take some time to materialize. Thus, we can distinguish between the equilibrium properties of the model and the transitional dynamics.

In the long run, in the absence of changes in the location specific variables, the economy converges to a situation in which workers are indifferent across locations and where factor prices, net of amenities per capita, are equalized across locations.[44] Initial conditions and labor flows determine the size of each location and the relative size of each skill in each location, determining the long-run equilibrium. In this long-run equilibrium there are still positive flows of internal migrants between the different regions. Net flows are, however, zero. In general, the equilibrium need not be unique: starting from different initial conditions, the economy may converge to different long-run equilibria.

When the steady state receives an unexpected shock then the economy changes and reaches a new steady state. The speed of convergence crucially depends on the relative importance that workers give to the idiosyncratic tastes versus the working conditions, governed by the variance of ϵ. If this variance is larger, then idiosyncratic tastes become more important, while if it is zero, only labor market conditions matter and adjustment takes place instantaneously.

[44] We can see this by equalizing bilateral flows, as I show later. I define amenities per capita as ${a_s}^{1/\lambda} = \frac{A_s^{1/\lambda}}{N_s}$.

The case of interest for the current paper is when there is an unexpected increase in the size of the low-skilled labor force in location s. In this case, the increase in L_s induces an instantaneous increase in the wage gap between high- and low-skilled workers in s. This makes location s attractive to high-skilled workers, while it make it less attractive for low-skilled workers in s. Thus, some high-skilled workers move towards s while some low-skilled workers move away from s.

Proposition 2. *An (unexpected) increase in L_s in s leads to:*

1. *An instantaneous decrease in w_s*
2. *An instantaneous increase in h_s*
3. *A relocation of low-skilled workers away from s*
4. *A relocation of high-skilled workers toward s*
5. *Gradual convergence of indirect utility across regions*

Proof. See the Appendix ☐

It is possible to write similar propositions for exogenous changes in either the amenity levels or the productivity parameters.

A final property of the model worth discussing is that if the different regions share the same technology, i.e., if $\theta_s = \theta \ \forall s \in S$ and the amenity levels are not dependent on skill levels, in the long-run equilibrium the aggregate economy looks like the canonical closed economy model with two skills discussed in Acemoglu and Autor (2011) and Katz and Murphy (1992). More concretely, we can define aggregate GDP as:

$$Q = \sum_s Q_s = \sum_s B_s[\theta H_s^\rho + (1-\theta)L_s^\rho]^{1/\rho} \tag{20}$$

Now, in the long-run equilibrium the share of high- and low-skilled workers will be the same in each location because indirect utilities are equalized across space. We can denote by ν_s this share. We can then re-write $H_s = \nu_s H$ and $L_s = \nu_s L$ and introduce this in the aggregate production function. H and L are the aggregate numbers of high- and low-skilled workers, respectively.

$$Q = (\sum_s \nu_s B_s)[\theta H^\rho + (1-\theta)L^\rho]^{1/\rho} \tag{21}$$

Note that aggregate TFP is a weighted sum of state TFPs. This is, in turn, a potential source of gains or losses from immigration at the national level. When there is an immigration shock there is some relocation away from high-immigration states, however, high-immigration states end, in the long run, with more population than lower immigration states (because some high-skilled are attracted to these states). If these high-immigration states have higher TFP than average, this could result in gains from immigration.

4.2.9 Calibration

The model can be used to explore various counterfactuals. First, I explain what would have happened if there had not been a Peso Crisis in late 1994. In this case Mexican immigration would have probably arrived at the same pace as in other years of the 1990s and wages would have not dropped significantly more in 1995 in California and other high-immigration states.

In the second counterfactual I analyze what would have happened if a state like Arizona had managed to effectively stop its inflow of Mexican immigrants. In this case, the direct effect of Mexican immigration would have disappeared and Arizona would have suffered the consequences of immigration only through the reallocation of natives after the shock in other states. Before doing these exercises, however, I describe how I calibrate the model to the data.

There are 3+51*4=207 parameters in the model: $\{\sigma, \lambda, \eta, \theta_s, A_s^h, A_s^l, B_s\}$. σ is the elasticity of substitution between high- and low-skilled workers in the production function. The wage regressions can be used to estimate this parameter. The estimates suggest that this elasticity is around 1, which I use in my calibration. By doing so, I am choosing a parameter that is within the range of parameters estimated in the wage regressions, but in the lower end. This implies that in the calibration I will find smaller wage effects than in the raw data, if the model is a good representation of reality and my estimates are accurate. There is an extra benefit in choosing $\sigma = 1$: the CES function collapses to the well known Cobb-Douglas case.

The second parameter is also estimated using the in-migration equations. The estimated coefficient in these regressions is $\frac{1}{\lambda}\frac{I_{st}}{N_{st}}$ in the model and around .2 in the data. Given that the in-migration rate is around 3-4 percent, a reasonable value of λ is between 1/10 and 1/5. I use the conservative value of $\lambda = 1/5$. In the Appendix I show that I obtain a similar parameter when using the Katrina shock instead of the Mexican one. Also, in Monras (2013a) I estimate a similar value, using an identification strategy relying on the 2008 crisis.

I calibrate the rest of the parameters to match Census data in 1990. In particular, I use the relative labor demand to calibrate θ_s for each state:

$$ln(h_s/w_s) = \frac{\theta_s}{1-\theta_s} - \frac{1}{\sigma} ln(H_s/L_s) \tag{22}$$

when $\sigma = 1$, i.e. when the production function is Cobb-Douglas, then, $\theta_s = 1/(1 + (w_s L_s / h_s H_s))$. In an aggregate economy this would also coincide with the share of high-skilled workers. While this need not be true at the state level, Figure 15 shows that there is also a tight relation between the share of high-skilled workers and the weight of high-skilled workers in the local production function.

The next set of parameters that I calibrate are the state-specific productivity levels. To find those I use the fact that, in perfect competition, the total wage bill should be equal to total production. Since total production is the productivity times the Cobb-Douglas production function, I can obtain productivities simply by dividing the total wage bill by the Cobb-Douglas production function given the θ_s and the worker levels in every state. Productivity levels align well with wage levels, as shown in Figure 16.

The final set of parameters that I calibrate are the amenity levels. To calibrate these I assume that the US is in spatial long-run equilibrium in 1990:

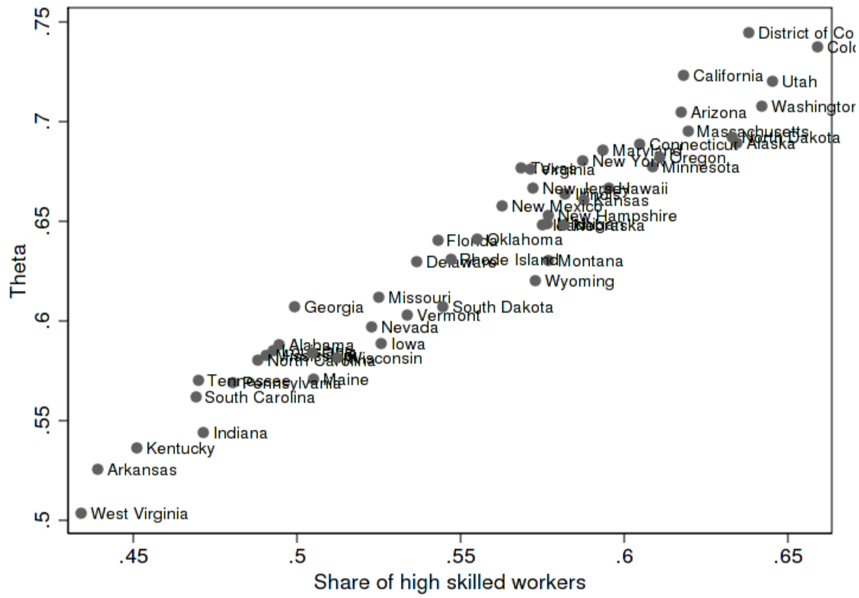
$$P_{s,s'} = P_{s',s}, \forall s, s' \in S \tag{23}$$

These equations allows me to obtain A_s, $\forall s$. For that we can use the definition of amenities per capita $a_s^{1/\lambda} = \frac{A_s^{1/\lambda}}{N_s}$ and simplify the algebra to obtain:

$$a_{s'}\omega_{s'} = a_s \omega_s \tag{24}$$

This equation allows me to obtain amenities, fixing a base location (in my case California). This equation also says that wages net of per capita amenities is equalized across regions, a natural feature in static spatial

Figure 15: Share of high-skilled workers and production technology



Notes: This figure shows the share of high-skilled workers and the calibrated θ_s in 1990.

equilibrium models (Glaeser, 2008).[45]

To obtain a value for η I match the internal in-migration rate in California (3 percent). A value of $\eta = .88$ accomplishes that.

4.2.10 Migration in the absence of the Peso Crisis

While at the beginning wage differences across space might be informative about the causal effect of immigration on wages, the shock then spreads to the rest of the economy leaving little spatial differences. The model introduced can help us think about what the longer run effects of immigration might be.

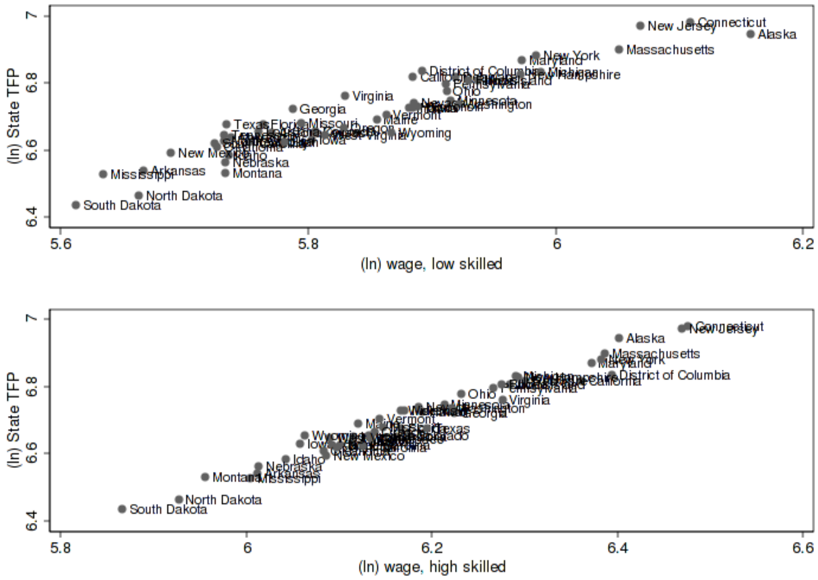
I present the results under two extreme scenarios. On the one hand I show what happens according to the model if nothing else other than reallocation accommodates Mexican immigration. As emphasized in Card and Lewis (2007), technology could have adapted to absorb changes in factor endowments, something ruled out here by keeping θ_s constant. In the model, this implies that positive Mexican inflows during the 1990s directly translate into decreases of wages of low-skilled workers in every state during this decade. An alternative assumption is that only unexpectedly large immigrant inflows matter. This is like assuming that "normal" Mexican inflows are absorbed through changes in the technology. The reality probably lies between these two extreme scenarios.

Following the comparison between California and New York introduced in the empirical section, Figure 17 shows what would have been the difference with and without the shock provoked by the Pesos crisis in late 1994 under the assumption that all inflows matter.

Figure 17 shows how wages of low-skilled workers decrease over the decade. They especially do so in

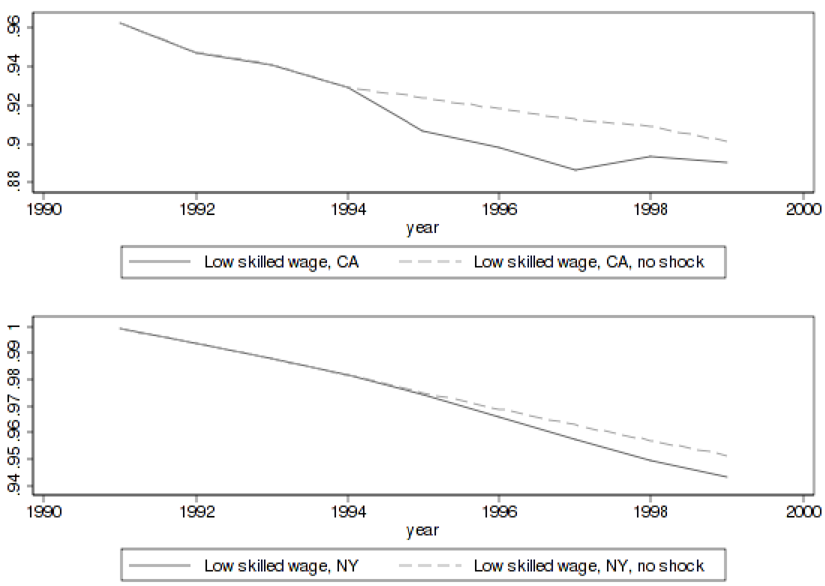
[45]Following on a previous footnote, this property does not hold if instead I assume that there are fixed costs of moving across regions.

Figure 16: Productivity levels and wages



Notes: This figure shows the productivity levels B_s and high- and low-skilled wages in 1990.

Figure 17: Counterfactual wage evolution

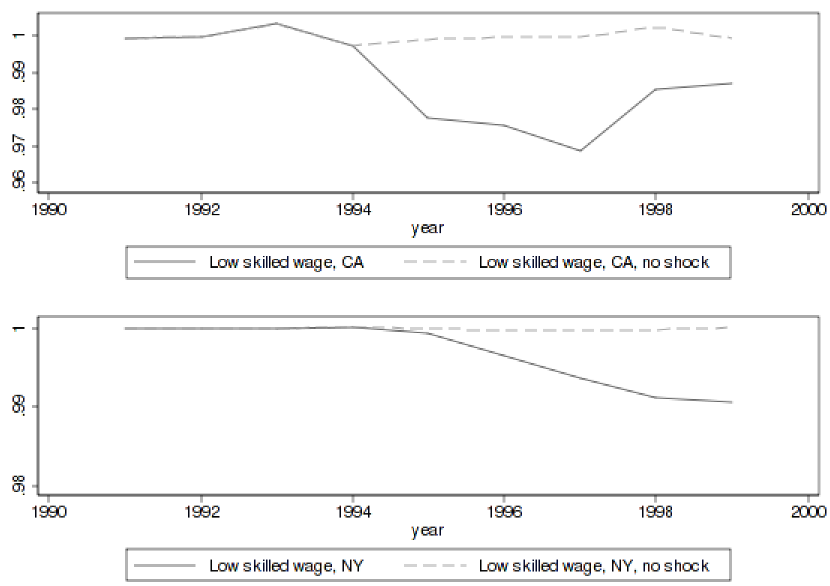


Notes: This figure shows the evolution of wages in the model with actual inflows of Mexicans and under the alternative that the Peso Crisis had not occurred. In this exercise, all inflows matter. This means that the accommodation of Mexican immigrants only occurs through labor reallocation across states.

high-immigration states like California, but internal migration ensures that these spill over to other states. In the long run, immigration affects all locations equally. Wage decreases of low-skilled workers vary from 10 percent in California to 5 percent in New York or even slightly lower in other states. These results imply a slightly higher effect of immigration on inequality than what was reported in Card (2009). As he argues, the key to this debate is whether high school drop-outs and high school graduates are perfect substitutes, something I have assumed here, and whether natives and immigrants are also perfect substitutes. Unlike Card (2009) I have shown that Mexicans and natives are probably perfect substitutes and this explains why immigration's effect on inequality is higher than what is discussed in Card (2009).

Figure 18 shows the case when only unexpected large inflows matter.[46] It shows that the unexpected large inflow of Mexican workers starting in 1995 decrease wages by around 3 percent in California and that wages start to recover in 1997. The drop is slightly smaller than in the observed data due to the fact that I calibrated the model to a slightly higher elasticity of substitution, but it captures very tightly the wage dynamics.

Figure 18: Counterfactual wage evolution



Notes: This figure shows the evolution of wages in the model with actual inflows of Mexicans and under the alternative that the Peso Crisis had not occurred. In this exercise, only inflows above average matter.

4.2.11 Migration with a restrictive policy in Arizona

In 2010 Arizona tried to adopt a law, the most controversial aspect of which was to allow officials to ask for residence permits if they had some suspicion that particular individuals were not legal residents. Given that a large fraction of Mexican immigrants in the US are undocumented, to some extent this is a policy that greatly reduces the incentives of Mexicans to move to Arizona. Other policies as well, like Operation

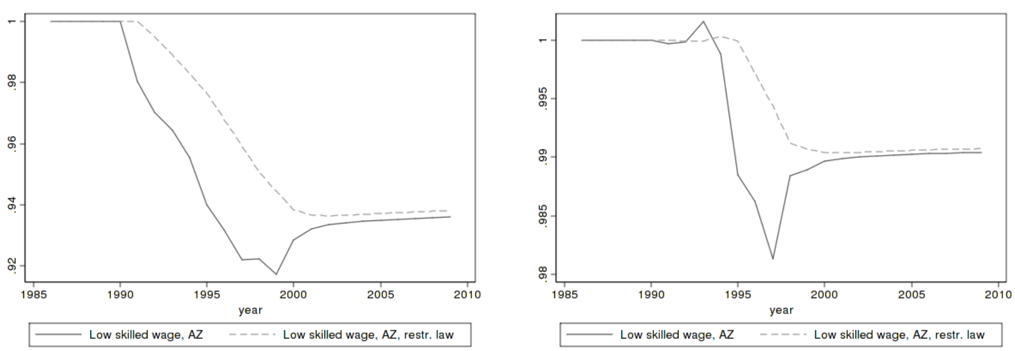
[46]This is the case when normal inflows of workers are absorbed though changes in the technology – the θ_s in my model – or changes in the use of capital that substitutes low-skilled labor – not modelled in my paper, but discussed extensively in Lewis (2012).

Hold the Line and Operation Gatekeeper, previously discussed, are policies intended to stop immigration into particular states.

Motivated by these policies, in this section I try to answer what would have happened in Arizona if Arizona had had a policy that had effectively stopped Mexican immigration in the 1990s. The link between the different states through internal migration, suggests that over the long run a single state can do little to avoid being affected by immigration. In this section I investigate what would be the short-run gains of such controversial policies.

As in the previous counterfactuals, I consider two alternative scenarios. In the first case I assume that overall inflows matter, while in the second case only inflows above average. I study the Mexican inflows of the 1990s, and then I assume that they stop in 2000 to see the long-run consequences. Figure 19 show these different wage dynamics. The exercises show that in the short run, in the worst years, Arizona's low-skilled wage was maybe 2 percent lower than what it would have been with a more restrictive immigration law. Wages are back to equilibrium soon after 2000. This suggests limited benefits from a unilateral law in one particular state to limit the amount of immigrants in that state.[47]

Figure 19: Counterfactual wage evolution



Notes: This figure on the left shows the evolution of wages in Arizona with actual inflows of Mexicans and under the alternative that Arizona had not received any Mexicans. In this exercise, all inflows matter. This means that the accommodation of Mexican immigrants only occurs through labor reallocation across states. This figure on the right shows the evolution of wages in Arizona with actual inflows of Mexicans and under the alternative that Arizona had not received any Mexicans. In this exercise, only inflows above average matter.

5 Conclusion

Existing literature on the causal effect of immigration on native wages seems to find contradictory evidence. On the one hand, evidence presented in various papers by Card and some other authors would suggest that immigration has a small effect on native wages. In the particular case of low-skilled US workers this would be a consequence of two important facts. First, if high school drop-outs and high school graduates are close substitutes in the production function then the pool of low-skilled workers absorbing low-skilled immigration into the US would be large, and thus aggregate wage effects small. Second, as first discussed in Ottaviano and Peri (2012), if low-skilled natives and immigrants are imperfect substitutes then former immigrants, not natives, absorb the labor supply shocks induced by newer immigrants.

[47]A recent paper (Watson, 2013) annalyses how immigrants respond to these type of policies by relocating within the US.

On the other hand, Borjas (2003) and some earlier papers question the evidence coming from comparisons of local labor markets because they argue that the US labor market is well integrated. When abstracting from geographic considerations, Borjas (2003) concludes that the effect of immigration on native workers is significantly larger than what we would conclude from Card (2009) or Ottaviano and Peri (2012).

In this paper, I use the Mexican crisis of 1995 as a novel push factor that brought more Mexicans than expected to historically high-immigration states to document the causal effect of immigration on native wages. Using this natural experiment I show that a 1 percent immigration-induced supply shock decreases wages by 1-1.5 percent on impact. This is substantially higher than was reported either by Card (2009) or by Borjas (2003), but in line with results I present from an alternative strategy using Hurricane Katrina as an exogenous push factor. This is a short-run effect.

Labor reallocation as a response to unexpected wage decreases ensures that immigration shocks spread across US regions. When the relative inflow of Mexicans increases by 1 percentage point, the share of low-skilled workers increases almost by 1 percent in the first year and then returns to its trend. This is due, primarily, to a decrease in in-migration rates, particularly of young low-skilled natives (a novel mechanism shown in this paper and in Monras (2013a)). This dissipates the shock across space, helping to explain why wage growth between 1990 and 2000 was only slightly lower in initially high-immigration states. At the same time, I have shown evidence that, when abstracting from geographic considerations like in Borjas (2003), age cohorts entering the labor markets in high-immigration years had significantly lower wage growth in the decade of the 1990s, which is in line with Oreopoulos et al. (Forthcoming). In other words, this paper documents how local shocks become national, an important step absent in Borjas (2003), and documents the causal effect of immigration in the short and long run.

Taken together, this evidence is consistent with the model presented in the last part of this paper, where I calibrated the model to US data and I showed how it can be used to answer policy-relevant counterfactuals. The first counterfactual analyzed in this paper is to study the wage evolution that would have occurred without the immigration shock. This allows me to evaluate over longer-time horizons the effect of immigration on low-skilled wages in every local labor market.

The second policy-relevant experiment studied in the paper tried to answer how effective a policy stopping Mexican migration into a particular state would be. The main insight from this exercise is to show how rapid internal reallocation spreads immigration shocks and, thus, the effects of such policies are likely to be limited.

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6 Appendix

6.1 Introduction to the Appendix

This is the appendix to the paper "Immigration and Wage Dynamics: Evidence from the Mexican Peso Crisis". I divide this appendix between empirics and theory. In the empirical section I report all the results that were left in the paper as robustness check. I also report the simple difference in difference exercise of looking at wages without relating them explicitly to Mexican labor inflows, but rather comparing high and low immigration states. In the theory section I proof the different propositions that are introduced in the paper and I extend the model to incorporate forward looking agents. The results in the empirical section may change slightly over the following weeks. I may also include some extra Tables or graphs.

6.2 Appendix, Empirical Section

6.2.1 Alternative instruments

In this section I show that I obtain the same results for the Mexican crisis independently on whether I use as instrument only one year after the shock hits, i.e. 1995, or if instead I consider the years 1996 and 1997 as part of the shock since Mexicans living in the US migrated less often back to Mexico during these years.

Specifically I can use either the interaction of the Mexican geographic distribution in 1980 with a dummy for 1995 or this interaction with dummies for 1996 and 1997 as well. Allowing different dummies for different years allows the intensity of the shock to be different across years. The results are shown in Table 12.

Table 12: The causal effect of Mexican immigration on low skilled wages

	Average Low Skilled Wage					
	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)
Mexican Inflow	-0.011 0.329	-1.457** 0.581	-1.013*** 0.372	-1.471*** 0.489	-1.134*** 0.387	-1.133* 0.623
Years in IV	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1999
State fixed effects	no	yes	yes	yes	yes	yes
Year fixed effects	no	yes	yes	yes	yes	yes
State specific trends	no	no	yes	no	yes	yes
Controls	no	no	no	yes	yes	yes
r2	-0.000	0.802	0.854	0.806	0.856	0.855
N	357	357	357	357	357	357
F-stat	121.107	644.861	1557.930	43.322	334.940	103.73

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995, a dummy for 1996 and another one for 1997. Panel regressions at the individual level on state level immigration inflows between years 1991-1999. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Robust standard errors clustered at the state level reported. Controls include: GDP of state, exports of state to Mexico, levels of low skilled young and old workers.

Table 12 shows that by including more time periods in the shock we obtain very similar results. My preferred specification is in columnes (3) and (5), since I include state specific trends in there. Column (6) in this table shows the estimate when using as instrument the interaction of the share of Mexicans in 1980 with a post shock dummy. They are all almost identical to the main specification in the text.

6.2.2 First stage Mincerian regressions and the exclusion of some regions

An alternative to the wage measure I use in the paper is to use the state fixed effects from a first stage mincerian regression. The results in this case are also similar. Table 13 shows them for the Mexican shock. It also shows that if we do not include California or Texas in the regressions the results do not change substantially. Nor do they change if instead of my preferred measure of Mexican inflows I use alternative measures by Passel et al. (2012) or by the INS and the DHS as reported in Hanson (2006).

Table 13: The causal effect of Mexican immigration on low skilled wages

	Composition Adjusted Low Skilled Wage						High Skilled Wage	
	IV	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mexican Inflow	-1.247*	-1.113***	-1.665*	-1.660***	-2.697**	-0.849*	0.532	0.629
	0.649	0.302	0.917	0.609	1.291	0.436	1.131	0.412
Data			Passel	INS+DHS			Passel	INS+DHS
State excluded	none	none	none	none	Cal.	Tx.	none	none
Controls and FE	yes	yes	yes	yes	yes	yes	yes	yes
r2	0.820	0.820	0.816	0.824	0.818	0.820	0.938	0.938
N	357	357	357	357	350	350	357	357
F-stat	103.160	334.940	52.275	135.443	245.514	2160.280	52.275	135.443

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995, a dummy for 1996 and another one for 1997. Panel regressions at the individual level on state level immigration inflows between years 1991-1999. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Robust standard errors clustered at the state level reported. Controls include: GDP of state, exports of state to Mexico, levels of low skilled young and old workers.

An important point is worth remarking however. When looking at wages in Texas, we only see the drop in wages when using Mincerian wage regressions to control for observable characteristics. The other high immigration states like Arizona and New Mexico follow wage patterns very similar to the ones shown for California in the main text, but since they are smaller states the series looks a little bit more noisy. Texas follows a similar pattern only when controlling for observable characteristics.

6.2.3 Worker heterogeneity: race, gender

Table 14 shows that the results do not change much either if we restrict the computation of wages to particular groups of individuals in the society, like only white men or women, or African American.

6.2.4 First difference and period lengths

In Tables 15 and 15 I estimate the following equation:

$$\Delta \ln w_{st} = \alpha + \beta \text{Relative Inflow}_{st} + \varepsilon st$$

where the Relative Inflow is measured as before and as in the paper and where I take yearly first difference as my dependent variable. In Table 15 I just look at the difference between years 1994 and 1995. This is a crossection in first difference like the one presented in Table 11 in the main text. It shows that in the short run the effect of and unexpected inflow might be much larger than in the 10 year differences. To see this, I show in this table the reduced form estimates of the share of Mexicans in 1980 on the dependent variable,

Table 14: The causal effect of Mexican immigration on low skilled wages

	Low Skilled Individual Wage					
	All	Non-hisp.	Non-hisp. males	Non-hisp. white	Non-hisp. females	Non-hisp. blacks
	IV	IV	IV	IV	IV	IV
Mexican Inflow	-0.467**	-0.941**	-1.062**	-0.916***	-0.789*	-2.633
	0.236	0.424	0.433	0.309	0.466	2.408
State fixed effects	yes	yes	yes	yes	yes	yes
State specific trends	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Individual Controls	yes	yes	yes	yes	yes	yes
Aggregate Controls	yes	yes	yes	yes	yes	yes
r2	0.349	0.371	0.362	0.392	0.349	0.254
N	37919	33856	19345	30511	14511	3345

Notes: All regressions instrument the relative inflow of Mexicans (Mexican inflow relative to young low skilled population in state) with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995. Panel regressions at the individual level on state level immigration inflows between years 1991-1999. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. 'Mexican Inflow' is the relative inflow of Mexicans to low skilled young natives using estimates for the inflow from the US Census 2000 (see text for more details). Wages are individual observations. Only young low skilled workers are included in the regressions. Regressions are weighted by the sample weight as introduced in (Ruggles et al., 2008). Controls include: GDP of state, exports of state to Mexico, levels of low skilled young and old workers.Robust standard errors clustered at the state level are reported.

then the OLS regression and finally the IV. The point estimates for younger workers are slightly hire than for the entire population, suggesting that if anything, younger workers were affected more than older ones. These estimates on the first differences are also slightly lower than in levels as presented in the text. In any case they are higher than in most of the literature.

Table 15: The causal effect of Mexican immigration on low skilled wages

	Reduced form: instrument on outcome variable					
	First Difference Wage					
	All Low Skilled		All High Skilled		Young Low Skilled	
	(1)	(2)	(3)	(4)	(5)	(6)
shock post	-0.758*	-0.949**	0.122	0.177	-0.799	-1.008
	0.396	0.410	0.411	0.432	0.627	0.665
Year	1995	1995	1995	1995	1995	1995
Controls	no	yes	no	yes	no	yes
r2	0.070	0.144	0.002	0.053	0.032	0.067
N	51	51	51	51	51	51

	OLS regressions					
	First Difference Wage					
	All Low Skilled		All High Skilled		Young Low Skilled	
	(1)	(2)	(3)	(4)	(5)	(6)
Mexican Inflow	-0.586**	-0.726**	0.110	0.140	-0.600	-0.748
	0.283	0.291	0.295	0.309	0.450	0.476
Year	1995	1995	1995	1995	1995	1995
Controls	no	yes	no	yes	no	yes
r2	0.081	0.158	0.003	0.054	0.035	0.070
N	51	51	51	51	51	51

	IV regressions					
	First Difference Wage					
	All Low Skilled		All High Skilled		Young Low Skilled	
	(1)	(2)	(3)	(4)	(5)	(6)
Mexican Inflow	-0.550**	-0.687***	0.089	0.128	-0.580**	-0.730**
	0.235	0.246	0.194	0.172	0.289	0.310
F-stat	180.776	197.344	180.776	197.344	180.776	197.344
Year	1995	1995	1995	1995	1995	1995
Controls	no	yes	no	yes	no	yes
r2	0.080	0.158	0.003	0.054	0.035	0.070
N	51	51	51	51	51	51

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for post 1995. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Robust standard errors clustered at the state level reported. Controls include: GDP of state, exports of state to Mexico, levels of low skilled young and old workers.

Table 16 show the same regression but extending the post shock period from 1995 only to 1995 to 1997. We see that while the effect is clearly present, the reallocation across space has already started to take place, making the estimated coefficients half as large as the one obtained in Table 15. In both Tables, we see that the effects are concentrated on low skilled workers.

Table 16: The causal effect of Mexican immigration on low skilled wages

	Reduced form: instrument on outcome variable								
	First Difference Wage								
	All Low Skilled			All High Skilled			Young Low Skilled		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shock post	-0.256***	-0.288**	-0.267**	-0.012	-0.010	0.008	-0.310***	-0.383***	-0.361***
	0.078	0.109	0.106	0.180	0.193	0.201	0.096	0.125	0.120
Years	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997
Controls	no	yes	yes	no	yes	yes	no	yes	yes
Time FE	no	no	yes	no	no	yes	no	no	yes
r2	0.009	0.043	0.075	0.000	0.009	0.042	0.006	0.053	0.080
N	153	153	153	153	153	153	153	153	153
	OLS regressions								
	First Difference Wage								
	All Low Skilled			All High Skilled			Young Low Skilled		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mexican Inflow	-0.217***	-0.237***	-0.220***	-0.035	-0.036	-0.021	-0.258***	-0.296***	-0.280***
	0.050	0.071	0.067	0.110	0.117	0.124	0.077	0.091	0.089
Years	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997
Controls	no	yes	yes	no	yes	yes	no	yes	yes
Time FE	no	no	yes	no	no	yes	no	no	yes
r2	0.037	0.056	0.081	0.002	0.011	0.042	0.034	0.073	0.095
N	153	153	153	153	153	153	153	153	153
	IV regressions								
	First Difference Wage								
	All Low Skilled			All High Skilled			Young Low Skilled		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mexican Inflow	-0.198***	-0.221***	-0.205***	-0.009	-0.008	0.006	-0.241***	-0.295***	-0.278***
	0.050	0.071	0.069	0.138	0.144	0.150	0.079	0.097	0.093
F-stat	179.909	221.180	218.642	179.909	221.180	218.642	179.909	221.180	218.642
Years	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997	1995-1997
Controls	no	yes	yes	no	yes	yes	no	yes	yes
Time FE	no	no	yes	no	no	yes	no	no	yes
r2	0.009	0.043	0.075	0.000	0.009	0.041	0.006	0.053	0.080
N	153	153	153	153	153	153	153	153	153

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for post 1995. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Robust standard errors clustered at the state level reported. Controls include: GDP of state, exports of state to Mexico, levels of low skilled young and old workers.

6.2.5 Share of Mexicans instead of Inflows

An alternative to use the inflow of Mexican workers is to use the share of Mexicans in the US labor force in the various local labor markets. This share, as discussed in the main text, has been increasing in the US over the years. This increase has been particularly important in high immigration states. This, as will be seen in the estimation, is crucial.

The main reason why in the main text I prefer the Mexican inflows over the share of Mexicans is because I can only compute the share of Mexicans using CPS data starting from 1994.

The specification that I use to estimate the effect of immigration on wages is the following:

$$\ln w_{st} = \alpha + \beta * \frac{\text{Stock of Mexicans}_{st}}{N_{st}} + \delta_t + \delta_s + t * \delta_s + \varepsilon_{st}$$

In this case, it is important to include the state-specific time trends to account for the different growth in the share of Mexicans across states.

Table 17 shows the results. Columns (5), (8) and (11) are pratically the same estimates than in the main text. This should convince reassure that using the Mexican inflows or the share of Mexicans is not driving the results, when appropriately including the state specific trends.

Table 17: The causal effect of Mexican immigration on wages

	Share of Mexicans		Los Skilled Native Wages								
	OLS	OLS	OLS	OLS	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
share of Mexicans			0.060	-0.326	-1.044***	-0.118	-0.753	-1.374***	0.054	-0.673	-1.579***
			0.098	0.318	0.360	0.136	0.655	0.470	0.097	0.646	0.611
Mexican Inflow	0.124	0.290									
	0.112	0.200									
shock per 1995	0.234***	0.274***									
	0.078	0.053									
State and year fixed effects	yes	yes	no	yes	yes	no	yes	yes	no	yes	yes
State specific trends	no	yes	no	no	yes	no	no	yes	no	no	no
Instrument	No instrument					Share Mex 1980 x shock			Share Mex 1980 x shock relative Mex inflows		
r2	0.989	0.994	0.004	0.780	0.861	-0.030	0.778	0.861	0.004	0.778	0.859
N	306	306	306	306	306	306	306	306	306	306	306
F-stat						83.004	5.642	103.192	203.003	6.531	52.284

Notes: Panel regressions at the state level between years 1994-1999. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Robust standard errors clustered at the state level reported.

6.2.6 Enrolment rates and immigration

It is possible that young low skilled respond to an inflow of low skilled workers by acquiring more education and leaving the pool of low skilled workers. This would be an attractive response to migration inflows. In this section I show that there is not a lot of support in the data suggesting that this is the case, at least when looking at short run responses. To evaluate this possibility I run a similar regression than the ones I use in the paper, but using enrolment rates as the dependent variable.

$$\text{Enrolment rate}_{st} = \alpha + \beta * \frac{\text{Labor Inflow}_{st}}{\text{N}_{st}} + X_{st} * \gamma + \lambda * t + \delta_s + \varepsilon_{st}$$

Table 18 reports various specifications for this regression. Column(1) reports the cross-sectional comparison. It is interesting that enrolment rates among native workers are higher in high immigration states. It is difficult to interpret this in a causal way. It could be that Mexican migrants are precisely going towards states whose native population is acquiring more education precisely because this gives them better opportunities in the labor market. It could also be that this positive coefficient is a native reaction to immigrant inflows. The instrumentation in column (7) of this cross-sectional comparison suggests that it may be more the former interpretation than the latter.

In columns (2)-(6) I play with including state fixed effects or state specific time trends. Unfortunately the results crucially depend on this, so it is hard to conclude whether immigrants seem to increase enrolment rates or not. I also play with including lagged or contemporaneous immigrant flows. It takes a little bit of time to get enrolled to some colleges so it would be more natural to observe effects on lagged immigrant inflows than on contemporaneous flows. I do not find this, and even less so when using my instrument in columns (8)-(14). This evidence seems to suggest that natives are not strongly responding to immigration shocks by acquiring more education.

Table 18: The causal effect of Mexican immigration on enrolment rates

	Enrolment rates													
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	IV	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Mexican Inflow	0.648**	0.880**	0.426			0.578	0.481	0.260	0.533	0.539			0.499	0.413
	0.314	0.340	0.385			0.491	0.430	0.200	0.734	0.730			0.612	0.624
L.Mexican Inflow				1.268*	-0.338	1.100	-0.539				0.099	-0.379	-0.182	-0.667
				0.650	0.899	0.739	0.977				0.579	0.640	0.797	0.812
State fixed effects	no	yes	yes	yes	yes	yes	yes	no	yes	yes	yes	yes	yes	yes
Year fixed effects	no	yes	yes	yes	yes	yes	yes	no	yes	yes	yes	yes	yes	yes
State specific trends	no	no	yes	no	yes	no	yes	no	no	yes	no	yes	no	yes
r2	0.045	0.617	0.738	0.620	0.737	0.622	0.738	0.029	0.617	0.738	0.615	0.737	0.615	0.738
N	357	357	357	357	357	357	357	357	357	357	357	357	357	357
F-stat								120.044	78.312	64.831	61.834	59.244	34.543	33.677

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995, a dummy for 1996 and another one for 1997. Panel regressions at the individual level on state level immigration inflows between years 1991-1999. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Robust standard errors clustered at the state level reported. Controls include: GDP of state, exports of state to Mexico, levels of low skilled young and old workers.

6.2.7 Difference-in-difference estimates of the wage effects, CPS data

As argued in the paper Mexican immigrants arriving to the US are both low skilled, young and arrived mainly to high immigration states. We can play with these three dimensions by defining three dummies. First, we can assume that workers, and in particular young workers are very mobile across the US, then the spatial dimension does not matter very much an we can write a Borjas (2003) type comparison by comparing the fortunes of young and old low skilled workers without considering where they live. A simple way to observe this is by running the following regressions:

$$lnwage_{it} = \alpha + \beta_1 * Young_{it} + \beta_2 * Shock_t + \beta_3 * Young_{it} * Shock_t + X_{it} * \beta + \gamma * time + \varepsilon_{it} \tag{25}$$

Second, we may want to assume that after all low skilled workers are not so mobile in the very short run and instead compare the fortunes of low skilled workers in high versus low immigration states by running the following regression:

$$lnwage_{it} = \alpha + \beta_1 * Shock_t + \beta_2 * HIS_{it} + \beta_3 * HIS_{it} * Shock_t + X_{it} * \beta + \gamma * time + \varepsilon_{it} \tag{26}$$

Third, we can be even more specific and limit the spatial comparison to young low skilled workers to see if those are indeed the most affected.

In these regressions $lnwage_{it}$ is the weekly wage of individual i at time t [48]. $Young_{it}$ is a dummy variable indicating whether individual i is young (i.e. less than 12 years of experience or younger than 31 years old) at time t. Similarly, HIS_{it} is a dummy indicating whether individual i lives in a high immigration state or not [49]. $Shock_t$ is a dummy for the time of the shock, i.e. 1995 through 1997. X_{it} is a vector of individual characteristics: race, gender, rural status, state fixed effects, metropolitan area fixed effects or metropolitan-state fixed effects. $time$ is a time trend. The sample of workers used in these regressions is full time full year low skilled workers.

The coefficient of interest is in all cases β_3. We expect $\beta_3 < 0$, so that young low skilled workers experienced a larger drop in their wage during the shock period relative to the control group. Similarly, we expect low skilled workers to suffer a larger drop in wages if they are working in a high immigration state than in a low immigration state. Table 19 reports results from running regressions (25) and (26).

[48] I obtain the same results irrespective of whether I use the real hourly wage or the weekly wage. The difference between them is that the weekly wage is constructed from the yearly income in the previous year and has more observations, while the hourly wage is the wage in the week when the CPS is conducted. I also obtain the same results irrespective of whether I include state-specific time trends or if I include or exclude the controls.

[49] High immigration states are the following: California, Arizona, New Mexico, Texas, Illinois and Florida

Table 19: Low skilled weekly wages by age and state

	Low Skilled Wage		High Skilled		Low Skilled Wage	
	All workers	Only no.Hisp	Wage		All workers	Only Young
shock	0.006	0.011	-0.013	shock	-0.007	-0.017
	0.008	0.008	0.010		0.005	0.011
young	-0.417***	-0.436***	-0.314***	HIS	-0.097***	-0.000
	0.010	0.013	0.009		0.021	0.029
young shock	**-0.025****	**-0.034*****	**0.000**	**HIS shock**	**-0.038****	**-0.047***
	0.010	0.012	0.013		0.015	0.025
Controls	yes	yes	yes	controls	yes	yes
State FE	yes	yes	yes	Occupation FE	yes	yes
r2	0.162	0.169	0.158	r2	0.213	0.273
N	147206	118700	60866	N	136384	28029

Note: ’shock’ is a dummy for the year 1995 and 1996. ’young’ is a dummy indicating whether individual is between 18 and 30 years old. ’HIS’ is a dummy indicating whether individual lives in a high immigration state. ’young shock’ and ’HIS shock’ is the interaction between the variables ’young¡ and ’shock’, and ’HIS’ and ’shock’, respectively. Weekly wages are constructed by dividing yearly wage by weeks worked for full time full year workers. Robust standard errors clustered at the state level. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Low skilled workers are high school drop outs and high school graduates. Hispanic workers are defined by the variable ’hispan’ in the CPS. Controls are observable characteristics in CPS data: race, urban status and gender and a time trend. Including or excluding the controls and the fixed effects does not change the results significantly.

In the first column of Table 19 I report the regression specified in equation 25 using the full sample, i.e. low skilled workers. While the shock did not have a negative effect on wages of all workers, it did decrease young low skilled worker's wage by 2.5%.

Column 2 drops the workers identified as hispanic by the CPS data. One may think that the drop in wages that I am reporting comes from a drop in the wages of former immigrants to the US, something suggested in the research by (Ottaviano and Peri, 2012), (Peri and Sparber, 2009), (Cortes, 2008) or (Card, 2009). Column 2 shows that when only considering non-Hispanic workers we also have that young low skilled worker's wage decreased by a bit more than a 3% during these two years defined as the shock. This result suggests that Mexican immigrant workers and young low skilled native workers are close to perfect substitutes.

The third column of Table 19 runs the same regression than column 1 but on high skilled workers only. The wage of young high skilled workers does not decrease during the shock years relative to the wage of old high skilled workers. This shows that the effect is only on young workers is only on low skilled and not on high skilled workers. In column 4 I run the regression presented in equation 26. I run this regression using the sample of low skilled workers [50]. Comparing high and low immigration states yields a result similar to the age comparison. In particular, low skilled workers in high immigration states have 3% lower wage than in low immigration states over these 2 years of the shock.

The last column, re-runs regression 26 but using young low skilled workers only. The sample size decreases substantially, but we can still obtain an estimate that indicates that young low skilled workers in high immigration states had on average a bit less than a 5% lower wage during the 2 years of the shock.

This table, thus, shows that the main effect of the shock on US wages is concentrated on young low skilled workers in high immigration states.

6.2.8 Difference in difference estimates using MORG CPS data

Another available data set is the Current Population Survey Outgoing Rotation Groups. Table 20 shows the results, in a number of different specifications. The coefficients are very similar to those in Table 19, since in Table 20 I report hourly wages.

6.2.9 Displacement in First Differences

In tis section I report the results of running the following regression:

$$\frac{\Delta L_{st}}{L_{s,t-1}} = \alpha + \beta * \frac{\text{Mex Inflow}_{st}}{L_{s,t-1}} + \varepsilon_{st}$$

This regression is similar to the one in the text but in first differences. Peri and Sparber (2011) argue that this is one of the better specifications to study labor reallocation.

The results of running this regression are shown in Table 21. Like most of the literature, when running OLS regression I obtain a coefficient of around .7. Any coefficient a below indicates that there is some labor reallocation. The closer the estimated coefficient to 1 the less reallocation there is. This .7 has been interpreted as a sign of low reallocation as a response to Mexican immigration. The first three columns show that this relationship between the growth of the Low skilled labor force in each location is increasingly less related to the Mexican inflows, the correlation moving from .78 to .61.

[50] The fact that there are fewer observations in column 4 compared to column 1 is due to the lack of information on the occupation of certain workers. If I do not include the occupation fixed effects in column 4 the results do not change and the

Table 20: The causal effect of Mexican immigration on low skilled wages

	(ln) Hourly Wage Low Skilled Workers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shock x his	-0.026***	-0.023***	-0.021***	-0.021***	-0.019***	-0.026***	-0.016***	-0.033***	-0.047**
	0.006	0.008	0.008	0.008	0.006	0.008	0.005	0.008	0.002
Years		1994-1996			1994-1995		1994-1996		
Controls	no	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	no	no	yes	yes	yes	yes	yes	yes	yes
State FE	no	no	yes	yes	yes	yes	yes	yes	yes
Sample					Full Time Workers				
Treatment			HIS: CA, TX, AZ, NM, IL				HIS: CA, TX, AZ		
Control			All others				All others except IL, NM		
States excluded				None			CA	TX	
Restricted to					None				NY and CA
r2	0.001	0.214	0.244	0.245	0.242	0.244	0.244	0.246	0.216
N	97365	97365	97365	97365	67666	92523	88890	88285	7969
	(ln) Hourly Wage High Skilled Workers								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
shock x his	-0.004	0.000	0.001	0.001	0.004	0.007	0.040***	-0.015*	-0.019
	0.015	0.016	0.017	0.017	0.019	0.022	0.010	0.008	0.004
Years		1994-1996			1994-1995		1994-1996		
Controls	no	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	no	no	yes	yes	yes	yes	yes	yes	yes
State FE	no	no	yes	yes	yes	yes	yes	yes	yes
Sample					Full Time Workers				
Treatment			HIS: CA, TX, AZ, NM, IL				HIS: CA, TX, AZ		
Control			All others				All others except IL, NM		
States excluded				None			CA	TX	
Restricted to					None				NY and CA
r2	0.004	0.191	0.216	0.217	0.219	0.217	0.210	0.217	0.199
N	77423	77423	77423	77423	53208	72959	68025	69704	8519

Notes: These table reports difference in difference estimates comparing high and low immigration states before and after the shock in 1995. The data is from the Merged Outgoing Rotation Groups of the Current Population Survey. Full time workers in the regression. 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Standard errors clustered at the state level are reported.

Table 21: The causal effect of Mexican immigration on labor reallocation

	Growth of Share Low Skilled Population							
	OLS	OLS	OLS	IV	IV	IV	IV	IV
growth share mex	0.785**			1.862***	0.984*	0.713		
	0.311			0.716	0.526	0.526		
L.growth share mex		0.733***					-0.448	0.087
		0.262					0.593	0.427
L2.growth share mex			0.618**					
			0.273					
Years in IV				1995	1995-96	1995-97	1996	1996-97
Years excluded							1995	1995
N	357	357	306	204	255	306	153	204
F-stat				144.273	155.065	97.675	197.403	117.732

Notes: 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels. Regressions are weighted by the sample weight as introduced in (Ruggles et al., 2008).

If we use 1995 as a year with an unusual high inflow of Mexican workers, we see, in column 4, that this increased the share of low skilled workers in the labor force by more than 1 to 1.[51] If we specify 1995 and 1996 as the shock periods, this coefficient drops to .98, while if we further include 1997 it drops to the usual

sample size coincides with that of column 1.

[51]Here I use data from CPS only.

.71. This indicates that there is some reallocation. Another way to look at it is by excluding 1995, and using 1996 and 1997 as the shock years. We observe that all the increase in labor force due to Mexican immigration in 1995, disperses across space in just 2 years.

Another possibility is to estimate the equation 5 in first difference using directly the available data at CPS:

$$\Delta \text{Share of low-skilled}_{st} = \alpha + \beta * \text{Total Relative Mexican Inflow}_{st} + Controls_{st} + \varepsilon_{st} \tag{27}$$

where the share of low-skilled workers is computed using both natives and immigrants and where I indicate the dependent variable as the 'Total Relative Mexican Inflow' to highlight that I divide the Mexican entrants by the total population – and not the low skilled population only.

Table 22 shows the results of estimating (27). The first three columns show the OLS regressions. These suggest a contemporaneous increase in the share of low skilled workers of almost one for one with the inflow of Mexicans. This is in line with the literature and it reflects the fact that, by the end of the 1990s, states that received more immigrants ended with (relatively) higher shares of low skilled workers (Card et al., 2008). The .7 estimate is the same than when running this same regression with Census data between 1990 and 2000.[52] These first 3 columns also show that the lagged effect on the increase in the share of low skilled workers is essentially 0. This means that upon arrival there is little reallocation or native displacement and there is no significant response the following year. The instrument captures whether this is still true in 1995. We observe that the share of low-skilled workers increases on for one with Mexican immigrants as in previous years, but then it decreases by 0.5 to 0.7 in 1996. Since we have seen that the inflow of Mexicans in 1995 was around 50 percent higher in 1995, this suggests that most of the extra immigrants are absorbed through reallocation in 1996. This means that reallocation takes place as a response of unexpectedly large inflows of low skilled workers, while normal inflows are partially absorbed though technology adoption and partly (though to a smaller extent) through labor reallocation. In this table I use only observations for 1994-1999 because I use numbers of Mexican inflows directly from CPS data. While for the wage regressions the concern was to underestimate the size of the shock, in this case using it would over estimate the response of the share of low-skilled workers, since a number of Mexicans would be missing from the computation of this share.[53]

6.3 Appendix, Theory Section

6.3.1 Proofs of propositions

In section 3.3 of the paper I make the claim that under the stated assumptions the derivative of (internal) in-migration rates with respect to (log) wages is approximately $\frac{1}{\lambda}\frac{I_s}{N_s}$. More specifically:

Proposition 3. *If ϵ_s^i are iid and follow a type I Extreme Value distribution with shape parameter λ then, in the environment defined by the model, we have that:*

1. $\partial(\frac{I_s}{N_s})/\partial \ln w_s \approx \frac{1}{\lambda}\frac{I_s}{N_s}$
2. $\partial(\frac{O_s}{N_s})/\partial \ln w_s > 0$*, but tends to 0 as the number of regions increases*

[52] I have done this exercise and I can show it upon request.

[53] In the Appendix I show the response of the share of low skilled workers and the share of native low skilled workers as shown in Figure 10 to the shock used for the wage regressions. The results are very much in line with the ones presented here.

Table 22: The causal effect of Mexican on the share of low-skilled workers

	Δ Share of low-skilled workers					
	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Mexican Inflow	0.692***	0.709***	0.710**	0.700*	1.208***	1.248***
	0.259	0.273	0.290	0.377	0.393	0.359
L.Mexican Inflow	0.040	0.055	0.077	-0.356	-0.556*	-0.690*
	0.159	0.170	0.235	0.295	0.307	0.409
N	255	255	255	255	255	255
F-stat				16.860	32.942	18.860
State and time FE	no	yes	yes	no	yes	yes
Controls	no	no	yes	no	no	yes
			First Stage			
			Mexican Inflow			
				OLS	OLS	OLS
				(4)	(5)	(6)
Predicted Mexican Inflow x shock				0.823***	0.847***	0.921***
				0.271	0.247	0.266
N				255	255	255
State and time FE				no	yes	yes
Controls				no	no	yes

Notes: All regressions instrument the relative inflow of Mexicans with the interaction of the share of Mexicans by state in 1980 and a dummy for 1995. Lagged variables are instrumented by the lagged instrument. Panel regressions at the state level between years 1991-1999. 3 stars represents 1 percent, 2 stars represents 5 percent and 1 star represents 10 percent significance levels. Robust standard errors clustered at the state level are reported. Controls include: GDP of state, exports of state to Mexico, levels of low-skilled young and old workers. 'L.' denotes lagged variable.

Proof. To proof this result note first the following:

$$lnP_{s,s'} = \eta + lnN_s + \frac{1}{\lambda}lnV_{s,s'} - ln(\sum_j e^{\frac{1}{\lambda}lnV_{s,j}})$$

Note also that $V_{s,s'}$ depends, up to some constants, on $w_{s'}$ exclusively. Thus,

$$\partial lnP_{s,s'}/\partial lnw_{s'} = 0 + \frac{1}{\lambda} - \partial(ln(\sum_j e^{\frac{1}{\lambda}lnV_{s,j}}))/\partial lnw_{s'}$$

Now $\partial(ln(\sum_j e^{\frac{1}{\lambda}lnV_{s,j}}))/\partial lnw_{s'}$ is approximately 0:

$$\partial(ln(\sum_j e^{\frac{1}{\lambda}lnV_{s,j}}))/\partial lnw_{s'} = \frac{1}{\sum_j e^{\frac{1}{\lambda}lnV_{s,j}}} * (1/\lambda) * \frac{\partial lnV_{s,s'}}{\partial lnw_{s'}} = \frac{1}{\sum_j V_{s,j}^{\frac{1}{\lambda}}} * (1/\lambda)$$

where the last equality comes from realizing that $\frac{\partial lnV_{s,s'}}{\partial lnw_{s'}} = 1$. The denominator in the last expression increases as the number of alternative locations increase. Thus $\partial(ln(\sum_j e^{\frac{1}{\lambda}lnV_{s,j}}))/\partial lnw_{s'}$ is approximately 0. We have then that $\partial lnP_{s,s'}/\partial lnw_{s'} \approx \frac{1}{\lambda}$. We can now use this to compute the elasticity of in and out-migration rates to changes in wages:

$$\frac{I_s}{N_s} = \frac{1}{N_s}\sum_{k \neq s} P_{k,s} = \frac{1}{N_s}\sum_{k \neq s} e^{lnP_{k,s}}$$

So,

$$\partial \frac{I_s}{N_s}/\partial lnw_s = \frac{1}{N_s}\sum_{k\neq s} e^{lnP_{k,s}} * \frac{\partial lnP_{k,s}}{\partial lnw_s} \approx \frac{1}{\lambda} * (\frac{1}{N_s}\sum_{k\neq s} P_{k,s}) = \frac{1}{\lambda}\frac{I_s}{N_s}$$

We can use similar algebra to proof point 2 of the proposition.

$$\frac{O_s}{N_s} = \frac{1}{N_s}\sum_{k\neq s} P_{s,k} = \frac{1}{N_s}\sum_{k\neq s} e^{lnP_{s,k}}$$

This is:

$$\frac{\partial lnP_{s,k}}{\partial lnw_s} = 0 + 0 - \frac{1}{\sum_j V_{s,j}^{\frac{1}{\lambda}}} * (1/\lambda)$$

So,

$$\partial(\frac{O_s}{N_s})/\partial lnw_s = \frac{1}{N_s}\sum_{k\neq s} e^{lnP_{s,k}}\frac{\partial lnP_{s,k}}{\partial lnw_s} = \frac{1}{N_s}\sum_{k\neq s} N_s p^i_{s,k}(\frac{-1}{\lambda\sum_j V_{s,j}^{\frac{1}{\lambda}}})$$

This can be simplified to:

$$\partial(\frac{O_s}{N_s})/\partial lnw_s = \frac{-1}{\lambda}(1 - p^i_{s,s})(\frac{1}{\sum_j V_{s,j}^{\frac{1}{\lambda}}})$$

And this last term is small and gets smaller the more locations available there are.

□

The second proposition in the paper states the following:

Proposition 4. *An (unexpected) increase in L_s in s leads to:*

1. *An instantaneous decrease in w_s*
2. *An instantaneous increase in h_s*
3. *A reallocation of low skilled workers away from s*
4. *A reallocation of high skilled workers toward s*
5. *Slow convergence of indirect utility across regions*

Proof. 1. is clear from looking at the local labor demand for low skilled workers:

$$w_s = p_s B_s(1-\theta_s) Q_s^{\frac{1}{\sigma}} L_s^{\frac{-1}{\sigma}} \tag{28}$$

Note that $\partial(\frac{1}{\sigma}lnQ_s)/\partial lnL_s = \frac{1}{\sigma}\frac{1}{Q_s^{\frac{\sigma-1}{\sigma}} L_s^{\frac{1}{\sigma}}}$ which is positive but smaller than $\partial(\frac{-1}{\sigma}lnL_s)/\partial lnL_s = \frac{-1}{\sigma}$.

2. is also clear from looking at the local labor demand for high skilled labor.

For 3. we only need to look at the first proposition. In-migration rates decrease towards s, while out-migration rates are close to 0 (though slightly positive), so s looses low skilled population. A similar argument can be made for 4. given the argument in 2.

5. is simply a consequence of what described in (1)-(4) and the fact that wages enter in indirect utility.

□

6.3.2 Extension of the model

In this section I introduce how it is possible to extend the model to incorporate forward looking agents in a simple (and still simplified) model.

Consumers maximise the utility given by:

$$E_t U^i_{s,t} = E_t \sum_{k=t}^{\infty} \beta^{t-k} (\text{arg max}_{s'} \{A_{s'} c^i_{s'} exp(\epsilon^i_{s'})\}) \tag{29}$$

subject to $c^i_{s'} \leq \omega^i_{s'}$.

This formulation follows the notation of the paper. This is, individual i living in state s at time t and choosing to move to s' consumes $c^i_{s'}$ from her wage $\omega^i_{s'}$. Unlike in the main model, individuals take into account the future at a discounted rate β. In the limiting case of $\beta = 0$ we are back to the model in the paper. Note that I have omitted time subscripts k.

We can re-write this problem using Bellman equations:

$$lnV(s_t) = ln(A_{s_t} \omega_{s_t}) + \beta E_t \{\text{argmax}_{s_{t+1}} \{lnV(s_{t+1}) + \epsilon^i_{s_{t+1}})\} + \epsilon^i_{s_t} \tag{30}$$

This equation just says that value for someone moving to $s_t \in \{1, .., S\}$ is the value of the amenities, the wage she gets at s_t.

Again, under suitable assumptions for the error term (i.e. extreme value distributed) we can simplify this expression (see a similar formulation in Pilossoph (2013)) we can use the following:

$$E_t \{max_{s_{t+1}} \{lnV(s_{t+1}) + \epsilon^i_{s_{t+1}})\} = \lambda ln \sum_{s_{t+1}} V(s_{t+1})^{1/\lambda}$$

So we obtained the simplified expression:

$$lnV(s_t) = ln(A_{s_t} \omega_{s_t}) + \beta \lambda ln \sum_{s_{t+1}} V(s_{t+1})^{1/\lambda} + \epsilon^i_{s_t} \tag{31}$$

This equation is almost identical to the one in the simplified model, with an extra term $\beta\lambda ln \sum_{s_{t+1}} V(s_t)^{1/\lambda}$ that summarizes the value of each location in the future. We can use this equation, as in the paper, to determine the internal flow of people to each location. The flow of people between locations will be exactly the same as the one analysed in the paper and in the first part of this appendix. The reason is simple. $\beta\lambda ln \sum_{s_{t+1}} V(s_t)^{1/\lambda}$ will cancel out in the bilateral flows across locations. This is:

$$V(s_t) = (A_{s_t} \omega_{s_t}) (\sum_{s_{t+1}} V(s_{t+1})^{1/\lambda})^{\lambda\beta} exp(\epsilon^i_{s_t}) \tag{32}$$

6.4 Appendix, data

In this section I give the details on how I constructed the aggregate net inflows from Mexico to the US.

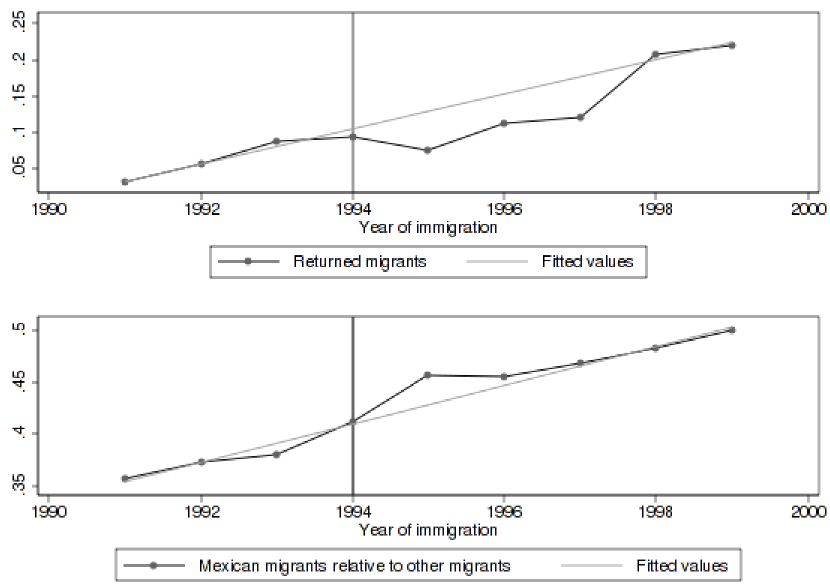
As said in the main text, I try to improve Passel et al. (2012) estimates in two dimensions. First, less Mexicans than usual might have returned to Mexico when the Mexican Pesos crisis started. Second, as pointed in Card and Lewis (2007), when immigrants answer on what year they arrived to the US when asked by the the US Census they tend to report years that are multiple of five more often.

To account for the first concern, I use Mexican Migration Project data. I use the people that were in Mexico after 2000 and that spent some time in the US during the 90s. I then compute what share of those arrived in each year of the 90s:

$$\text{Share returned to Mexico}_t = \frac{\text{Mexicans in Mexico who returned at } t}{\text{Mexican who were in the US in the 90s}}$$

This gives me the top panel of Figure 20.

Figure 20: Mexican emigration to the US by year of arrival



Note: The top panel shows the share of Mexicans residing in Mexico in the 2000s that claim to have returned to Mexico in the 90s, by year of arrival. The lower panel shows the share of Mexicans residing in the US in 2000 by year of arrival, relative to immigrants from other destinations.

For the second concern, I compute the number of Mexicans in the US that in the 2000 US Census report arriving in the US before time t relative to all low skilled immigrants:

$$\text{Share Mexicans in the US}_t = \frac{\text{Mexicans in the US in 2000 that arrived before time } t}{\text{All immigrants in the US in 2000 that arrived before time } t}$$

This is shown in the bottom panel of Figure 20. The two graphs have an upward trend. In the first case, the upward trend can be explained by the death rates, the changing stocks of Mexicans in the US and circular migration. Someone returning to Mexico in the early 90s is more likely to have died in the 2000s, more likely to have re-emigrated to the US and is drawn from a smaller pool of people (Mexicans in the US in the 90s) than people that return to Mexico. Similarly, the upward trend in Mexicans relative to the US could be explained by higher frequency of Mexicans in the US returning to Mexico. Mexico is closer to the US relative to other states, so returns to the home country might be more frequent than in countries that are further apart. This might mean that someone migrating from Mexico migrating to the US in the early 90s might be more likely to have returned than a similar migrant from another country of origin. I assume that there is no upward or downward trend in this series, by de-trending them. I define the deviations from the trend as the series minus the expected value of the series evaluated using a linear regression that does not include the years of the shock (the straight lines in Figure 20).

$$\hat{D}^I_t = \text{Share returned to Mexico}_t - \hat{A}^I - \widehat{trend}_I * t$$

$$\hat{D}^O_t = \text{Share Mexicans in the US}_t - \hat{A}^O - \widehat{trend}_O * t$$

I can then compute the percentage deviation from trend for both series by dividing by the expected value from the fitted regression. This is:

$$\hat{d}^I_t = \frac{\hat{D}^I_t}{\hat{A}^I + \widehat{trend}_I * t}$$

$$\hat{d}^O_t = \frac{\hat{D}^O_t}{\hat{A}^O + \widehat{trend}_O * t}$$

I finally assume that the net immigration flow has no trend, i.e. it is the average inflow on the decade of around 370,000 people a year, and that the deviations from the trend are given by the deviations of the trend from my measures that tried to account for inflows and outflows of Mexican immigrants to the US. This is:

$$\widehat{Mex}_t = (1 + \hat{d}^I_t - \hat{d}^O_t) * (\text{Average net Mexican inflow in the 90s})$$

Again, the numbers I obtain rest on the assumption that there isn't an upward trend in the number of Mexicans arriving to the US during the 90s. This may not be true, but it should not affect may estimates to the extent that I include year fixed effects or time trends.

6.5 Appendix, revisiting the Mariel Boatlift

6.5.1 Summary of the exercise

In this exercise I annlyse whether the findings in Card (1990) are inconsistent with my findings using the Peso Crisis experiment. The check is built in the following steps. First I replicate Card (1990) results. Then I show how his results are robust to distinguishing between high and low skilled workers (defined as below or above high school graduation). His standard errors, however, cannot rule out an effect on Miami's wages. I, then, replicate Card (1990) paper with the March CPS data. Again I confirm his results. However, if I distinguish between low and high skilled in the March CPS data I find point estimates that are very much in line with my own results using the Peso Crisis.

6.5.2 The Mariel Boatlift experiment

In April 1980, Fidel Castro allowed Cubans willing to emigrate to do so from the port of Mariel. These Cubans were relatively low skilled, some of them released from prisons and mental hospitals (Card, 1990). Around 125,000 Cubans migrated to the US between late April 1980 and October 1980 or June 1981 (Card, 1990). Around half of those probably settled in Miami. Card (1990) uses this natural experiment to assess the effect of immigration on the labor market.

6.5.3 Summary Statistics

Table 23 replicates some of Card (1990) numbers in his Table 1, in the published version. To construct these statistics I use the two data sets available, the March CPS and the CPS MORG. Card (1990) use the CPS MORG. His exact numbers are replicated in the bottom part of Table 23. In particular he uses the earnings weight, resulting in a estimate for Miami's population of 928,399 individuals. This is very close to the same number obtained using March CPS data, which, as shown in the Table is 927,247 individuals.

Table 23: Summary Statistics, Miami 1979

	March CPS				
	whites	black	cubans	hispanics	all
Population	337,955	224,138	260,803	85,855	927,247
Full Time workers	187,441	111,794	146,848	39,332	488,149
In Labor Force	258,144	159,314	203,397	64,354	695,914
Unemployed	13,039	7,710	12,927	4,835	39,676
Shares in Population	36.45%	24.17%	28.13%	9.26%	100.00%
Shares in Full Time Workers	38.40%	22.90%	30.08%	8.06%	100.00%
Unemployment Rate	6.96%	6.90%	8.80%	12.29%	8.13%
Percent of Full Time workers	55.46%	49.88%	56.31%	45.81%	52.64%
Percent in Labor Force	76.38%	71.08%	77.99%	74.96%	75.05%
	CPS MORG				
Population (final weight)	313,425	239,256	249,871	100,939	911,147
Population in Labor Force (final weight)	237,851	163,614	193,101	69,607	626,591
Percent in Labor Force (final weight)	75.89%	68.38%	77.28%	68.96%	68.77%
Population (earnings weight)	319,268	244,060	252,373	102,868	928,399
Population in Labor Force (earnings weight)	241,296	166,619	194,749	70,764	678,213
Percent in Labor Force (earnings weight)	75.58%	68.27%	77.17%	68.79%	73.05%

Notes: The summary statistics in CPS MORG coincide with Card (1990) when using the earnings weight.

The various statistics computed almost completely coincide across data sets. The only significant divergence is the number of non-Cuban Hispanics, in the March CPS data slightly lower by around 15,000 individuals. Also the percentage of them in the labor force coincides almost perfectly. Again, only Hispanic workers seem to be more in the labor force than in the CPS MORG sample.

In what follows, when I use the CPS MORG data I use Card (1990) sample. When using the March CPS I use the full time workers as defined in Acemoglu and Autor (2012).[54]

6.5.4 Wages in Miami vs. control group

Table 3 in Card (1990) reports the real hourly wage in Miami and a group of comparison cities (Los Angeles, Tampa, Houston and Atlanta) that Card (1990) picked because of similar black population and employment evolutions in the late 70s. While he does not report a statistical test to tell whether wages in Miami decreased in 1980 or not relative to the control group cities, by looking at the numbers there is no clear change or effects in Miami. He reports the numbers distinguishing by whites, blacks, hispanics, and Cubans. I follow the same categories except that I also report the numbers for all the population and I distinguish the Hispanic-Non Cubans in two groups, the ones of Mexican origin and the ones where the origin is not identified in CPS data. This last group has some observations that look like outliers, as it will become apparent later on.

Data details

Unfortunately I have not been able to replicate the exact average wages Card (1990) reports in his paper. There are several variables in the CPS MORG files that can be used:

[54] I use the weekly wage when using the March CPS as it has lower error, see Lemieux (2006). None of the results changes when instead using hourly wages from March CPS.

1. *earnwke*: Edited or computed earnings per week in this job. Includes overtime tips and commissions. For hourly workers, computed Item 25a times Item 25c appears here. For weekly workers, edited Item 25d appears here.

2. *earnhr*: Item 25c. "How much does ...earn per hour?" (in pennies). This is truncated so that when multiplied by usual hours the result is never more than $100,000 per year. Also, in some ye ars a maximum of 9900 is enforced. For 1979 to 1984 earnhr and earnhre are top coded at 99.99. For 1985 on, the top code depends on hours worked and is selected so that earning per hour times usual hours is not more than 1923.07 per week. Examining the data reveals that the top code is not uniformly applied. While there is always a density peak at the top code amount, a similar number of observations are generally present at higher wage rates. Take caution by testing for wages at or above the top code, if appropriate. Tips are not included.

3. *earnhre*: Edited Item 25c. "How much does ...earn per hour?" (in pennies)

4. *uearnhwk*: Item 25d. "How much does...usually earn per week at this job before deductions?" (in dollars) Includes overtime tips and commissions. Use this field (or uearnwke) for hourly workers.

5. *uearnhwke*: Edited Item 25d.

There are also several measures of hours worked in a week if we want to convert weekly wages to hourly wages:

1. *hourslwa*: Unedited Item 20a. "How many hours did...work last week at all jobs?"

2. *uhours*: Unedited Item 25a. "How many hours per week does...USUALLY work at this job?" (Main job)

3. *uhourse*: Edited Item 25a. "How many hours per week does...USUALLY work at this job?" [1989 trough 1993 the range is 1-99.] The allocation flag for this variable is noted with the earnings variables above. For 1994 on the job is the 'main job' and the answer 'hours vary' is translated to missing in the extracts.

Following the documentation in the NBER website (http://www.nber.org/morg/docs/cpsx.pdf and http://www.nber.org/r the recommended wage rate measure should be *earnwke/uhourse*. Many authors, see Lemieux (2006), usually drop outliers by dropping hourly wages below $1 and above $100 in 1979 dollars.

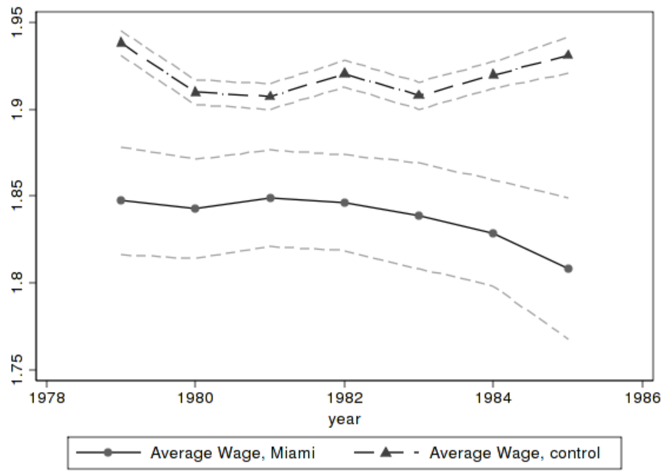
Replication of Card (1990) results on wages in figures, MORG data

Using the measure of hourly wages recommended by the NBER documentation I obtain the evolution of wages for white people in Miami and in the comparison group Card (1990) uses. This is shown in Figure 21.

This is almost identical to Card (1990) results reported in his Table 3. A visual inspection that will be reaffirmed later in the empirical exercises suggests that:

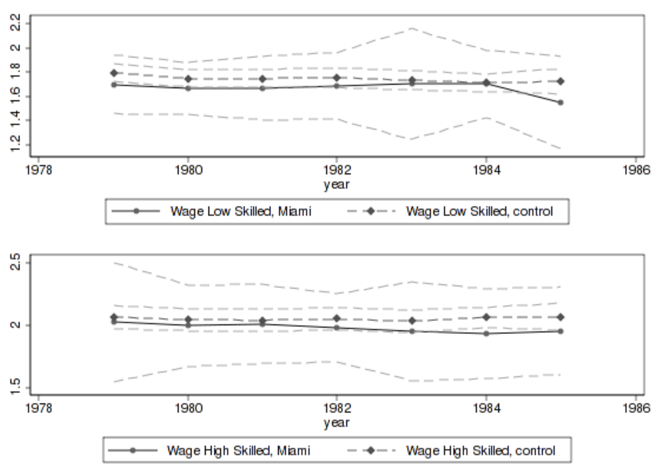
Result 5. *There is little evidence that wages dropped in Miami in 1980 when the Marielitos arrived when using CPS MORG data.*

Figure 21: Evolution of hourly wages of white workers



Note: CPS MORG data. This graph shows the hourly wage rate evolution of white workers in Miami and the control group of four cities: Tampa, Los Angeles, Houston and Atlanta. Dashed lines indicate the standard error of the computed average wage.

Figure 22: Evolution of hourly wages of white workers, by skill



Note: CPS MORG data. This graph shows the hourly wage rate evolution of white workers in Miami and the control group of four cities: Tampa, Los Angeles, Houston and Atlanta.

When I break this sample between high and low skilled workers, where the cutoff is defined by having more than high school or not I obtain the following graph:

Figure 22 provides suggestive evidence that wages of white low skilled workers were not differentially affected by the Cuban inflows relative to either the high skilled whites or the low skilled in the comparison cities. Dashed lines indicate the standard error of the computed average wage.

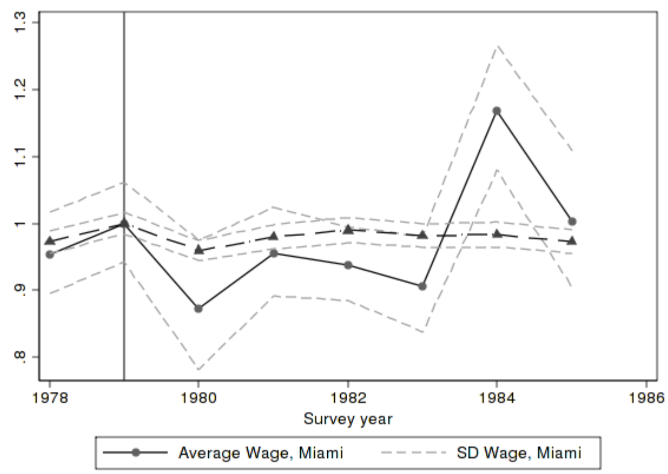
Result 6. *When distinguishing between high and low skilled workers in CPS MORG data there is little evidence that the Mariel boatlift affected wages.*

Replication of Card (1990) results on wages in figures, March CPS data

In this section I repeat the figures previously shown, but using instead March CPS data instead of CPS MORG.Instead of using hourly wages, I use weekly wages. In March CPS data is is probably a preferred measure of wages, because of the noise in the variable reporting the usual hours worked in the previous year, particularly for early years.

Figure 23 shows the wage evolution of the white population in Miami and the control groups.

Figure 23: Evolution of weekly wages of white workers



Note: March CPS data. This graph shows the wage evolution of white workers in Miami and the control group of four cities: Tampa, Los Angeles, Houston and Atlanta. Dashed lines indicate the standard error of the computed average wage. Weekly wages are computed for full year workers using yearly income and weeks worked. Wages are normalized to 1979 for easy comparison.

In Figure 23 we observe that average wages if anything decreased in 1980, precisely when Miami received the labor supply shock. The magnitude of the shock is disputable, since it is diffuclt to know how many of the Mariel Boatlift immigrants were actually ready to enter the labor market. A 7% is probably an upper bound. The graph suggests a drop in average wages of around 10%.

We can further break down the wage evolution between high and low skilled workers. This is shown in Figure 24.

Figure 24 shows that the drop in wages shown in Figure 23 comes from a drop in wages of the low skilled of almost 20% and and *increase* in wages of high skilled workers of a bit under 10%. The implied labor demand elasticity for low skilled workers from these raw estimates would not be far from 1, as found in Monras (2013b).

Result 7. *When using March CPS data there is some suggestive evidence that the labor supply shock caused by the inflow of Cuban workers decreased wages of low skilled workers.*

6.5.5 Regressions using March CPS data

To statistically assess this I use the following difference in difference regression. The idea is simply to compare the wages in Miami and the control cities before and after the shock:

Figure 24: Evolution of weekly wages of white workers, by skill

Note: March CPS data. This graph shows the wage evolution of white workers in Miami and the control group of four cities: Tampa, Los Angeles, Houston and Atlanta. The top panel shows low skilled wages, while the bottom shows high skilled wages. Dashed lines indicate the standard error of the computed average wage. Weekly wages are computed for full year workers using yearly income and weeks worked. Wages are normalized to 1979 for easy comparison.

$$\ln \text{wage}_{ist} = \alpha + \beta_1 \text{Miami}_{is} \text{ x } \text{Shock}_t + \beta_2 \text{Miami}_{is} + \beta_3 \text{Shock}_t + (+\delta_t + \delta_s) + \varepsilon_{ist}$$

where the i indicates individuals, s metropolitan areas, t time, δ fixed effects, $Miami_{is}$ indicates if individual i lives in Miami, and $Shock_t$ is a dummy taking value 1 in 1980 onwards. It is important to note all these regressions should be interpreted with caution (Bertrand et al., 2004) and Donald and Lang (2007). The reported standard errors are the standard errors obtained from the simple OLS regression.

Tables 24-26 show the exercise for 1978-1981. Every table has the same structure but different periods lengths. In Table 24 I include only 1979 and 1980. In Table 25 I include an extra pre-shock year, while in Table 26 I include year before and two after the shock.

In columns (1)-(4) I include the entire working age population, first without controls, then with individual characteristics (experience, experience square, dummies for gender, race and hispanic origin), then with year fixed effects, then with metropolitan area fixed effects. In Columns (5)-(9) I do the breakdown by race/hispanic origin. Each table has three panels. The top panel includes all the population, while the middle one includes low skilled workers and the bottom one only high skilled workers.

The first thing we see in Table 24 is that the precision of the estimates is not great. The number of observations and the variance in the US distribution makes it hard to distinguish the wage evolution in Miami from that of the control group. The point estimates show what was illustrated in Figures 23 and 24. When pooling all the workers together we see that the point estimates indicate a small decrease in wages in Miami relative to the control group of between 0 to 4 percent (Columns (1)-(4)). When we distinguish the workers between high and low skilled we see that the estimated effect of the shock on low skilled workers is between -7 to -8 percent. Instead the wage of high skilled workers is estimated to increase by 4 to 7 percent. The numbers are similar in the other Tables.

Table 24: The causal effect of a local labor supply shock on wages

	Dependent Variable: (ln) Weekly Wage								
	All workers age 16-61								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	-0.008	-0.038	-0.038	-0.037	-0.102	0.059	0.117	-0.049	0.086
	0.061	0.056	0.056	0.056	0.121	0.165	0.261	0.089	0.185
N	5615	5615	5615	5615	3076	1192	335	687	93
	All workers age 16-61, High School or less (Low Skilled workers)								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	-0.068	-0.079	-0.079	-0.078	-0.228	-0.237	0.032	-0.008	-0.087
	0.079	0.077	0.077	0.077	0.210	0.181	0.338	0.110	0.251
N	3232	3232	3232	3232	1444	37	239	412	48
	All workers age 16-61, Strictly more than High School (High Skilled workers)								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	0.068	0.044	0.044	0.043	0.027	0.726	0.241	-0.156	0.316
	0.088	0.078	0.078	0.078	0.121	0.760	0.153	0.193	0.208
N	2383	2383	2383	2383	1632	13	96	275	45
Individual Controls	no	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	no	no	yes	yes	yes	yes	yes	yes	yes
City FE	no	no	no	yes	yes	yes	yes	yes	yes
Population in Sample	All All				Whites	Mexican Hisp.	Cuban	Black	Other Hisp.
Sample restriction	All workers that report working full time and at least 40 weeks, have a valid wage and are not self empl.								
Years in Sample	1979-1980								
Data source	March CPS								

Notes: 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels.

Table 25: The causal effect of a local labor supply shock on wages

	Dependent Variable: (ln) Weekly Wage								
	All workers age 16-61								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	-0.011	-0.031	-0.030	-0.030	-0.086	0.067	0.233	-0.052	0.030
	0.056	0.052	0.052	0.052	0.116	0.154	0.198	0.077	0.187
N	8231	8231	8231	8231	4567	1689	482	1009	145
	All workers age 16-61, High School or less (Low Skilled workers)								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	-0.043	-0.039	-0.039	-0.038	-0.137	-0.313*	0.188	-0.006	-0.078
	0.074	0.073	0.073	0.073	0.204	0.175	0.316	0.099	0.198
N	4760	4760	4760	4760	2162	48	345	630	69
	All workers age 16-61, Strictly more than High School (High Skilled workers)								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	0.021	-0.009	-0.008	-0.007	-0.025	0.695	0.226	-0.204	0.253
	0.080	0.072	0.072	0.072	0.114	0.763	0.189	0.141	0.297
N	3471	3471	3471	3471	2405	16	137	379	76
Individual Controls	no	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	no	no	yes	yes	yes	yes	yes	yes	yes
City FE	no	no	no	yes	yes	yes	yes	yes	yes
Population in Sample	All All				Whites	Mexican Hisp.	Cuban	Black	Other Hisp.
Sample restriction	All workers that report working full time and at least 40 weeks, have a valid wage and are not self empl.								
Years in Sample	1978-1980								
Data source	March CPS								

Notes: 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels.

Table 26: The causal effect of a local labor supply shock on wages

	Dependent Variable: (ln) Weekly Wage								
	All workers age 16-61								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	-0.025	-0.026	-0.026	-0.024	-0.030	0.088	0.140	-0.106*	0.070
	0.041	0.036	0.036	0.036	0.074	0.125	0.164	0.062	0.168
N	10994	10994	10994	10994	6071	2243	658	1390	178
	All workers age 16-61, High School or less (Low Skilled workers)								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	-0.068	-0.060	-0.060	-0.057	-0.068	0.031	0.177	-0.117	-0.124
	0.049	0.047	0.047	0.047	0.120	0.172	0.252	0.078	0.182
N	6320	6320	6320	6320	2834	73	464	860	89
	All workers age 16-61, Strictly more than High School (High Skilled workers)								
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
miami x post	0.038	0.012	0.012	0.014	0.019	1.434*	0.073	-0.184	0.317
	0.065	0.058	0.058	0.058	0.087	0.757	0.185	0.120	0.296
N	4674	4674	4674	4674	3237	21	194	530	89
Individual Controls	no	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	no	no	yes	yes	yes	yes	yes	yes	yes
City FE	no	no	no	yes	yes	yes	yes	yes	yes
Population in Sample	All All				Whites	Mexican Hisp.	Cuban	Black	Other Hisp.
Sample restriction	All workers that report working full time and at least 40 weeks, have a valid wage and are not self empl.								
Years in Sample	1978-1981								
Data source	March CPS								

Notes: 3 stars is 1%, 2 stars is 5% and 1 star is 10% significance levels.