Online Appendix to "Immigration and Wage Dynamics: Evidence from the Mexican Peso Crisis"

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PRELIMINARY AND INCOMPLETE

1 Introduction

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.

2 Appendix, Empirical Section

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.

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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 1.

Table 1: 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	-1.457**	-1.013***	-1.471***	-1.134***	-1.133*
	0.329	0.581	0.372	0.489	0.387	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 1 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.

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 2 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 2: 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.

2.3 Worker heterogeneity: race, gender

Table 3 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.

2.4 First difference and period lengths

In Tables 4 and 4 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 4 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

Table 3: 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.

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, 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 4: 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 5 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 4. In both Tables, we see that the effects are concentrated on low skilled workers.

Table 5: 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.

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 6 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 6: 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.

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 7 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 7: 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.

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:

$$lnwage_{it} = \alpha + \beta_1 * Young_{it} + \beta_2 * Shock_t + \beta_3 * Young_{it} * Shock_t + X_{it} * \beta + \gamma * time + \varepsilon_{it} \quad (1)$$

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:

$$lnwage_{it} = \alpha + \beta_1 * Shock_t + \beta_2 * HIS_{it} + \beta_3 * HIS_{it} * Shock_t + X_{it} * \beta + \gamma * time + \varepsilon_{it} \quad (2)$$

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 [1]. $Young_{it}$ 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 [2]. $Shock_t$ 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 8 reports results from running regressions (1) and (2).

[1] 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.

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

Table 8: 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 'youngÂ¡ 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 8 I report the regression specified in equation 1 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 8 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 2. I run this regression using the sample of low skilled workers [3]. 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 2 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.

2.8 Difference in difference estimates using MORG CPS data

Another available data set is the Current Population Survey Outgoing Rotation Groups. Table 9 shows the results, in a number of different specifications. The coefficients are very similar to those in Table 8, since in Table 9 I report hourly wages.

2.9 Displacement in First Differences

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

[3]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 sample size coincides with that of column 1.

Table 9: 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.

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

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 10. 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.

If we use 1995 as a year with an unusual high inflow of Mexican workers, we see, in column 4,

Table 10: 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).

that this increased the share of low skilled workers in the labor force by more than 1 to 1.[4] 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 .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 **??** in first difference using directly the available data at CPS:

$$\Delta\text{Share of low-skilled}_{st} = \alpha + \beta * \text{Total Relative Mexican Inflow}_{st} + Controls_{st} + \varepsilon_{st} \quad (3)$$

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 11 shows the results of estimating (3). 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.[5] 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

[4]Here I use data from CPS only.
[5]I have done this exercise and I can show it upon request.

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.[6]

Table 11: 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.

[6] 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 **??** to the shock used for the wage regressions. The results are very much in line with the ones presented here.

3 Appendix, Theory Section

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 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. 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 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 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:

$$w_s = p_s B_s(1-\theta_s)Q_s^{\frac{1}{\sigma}} L_s^{\frac{-1}{\sigma}} \tag{4}$$

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.

□

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:

$$E_t U^i_{s,t} = E_t \sum_{k=t}^{\infty} \beta^{t-k} (\text{arg max}_{s'} \{A_{s'} c^i_{s'} exp(\epsilon^i_{s'})\}) \tag{5}$$

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:

$$lnV(s_t) = ln(A_{s_t} \omega_{s_t}) + \beta E_t \{\text{argmax}_{s_{t+1}} \{lnV(s_{t+1}) + \epsilon^i_{s_{t+1}})\} + \epsilon^i_{s_t} \tag{6}$$

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:

$$lnV(s_t) = ln(A_{s_t} \omega_{s_t}) + \beta \lambda ln \sum_{s_{t+1}} V(s_{t+1})^{1/\lambda} + \epsilon^i_{s_t} \tag{7}$$

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:

$$V(s_t) = (A_{s_t}\omega_{s_t})(\sum_{s_{t+1}} V(s_{t+1})^{1/\lambda})^{\lambda\beta} exp(\epsilon^i_{s_t}) \tag{8}$$

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:

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

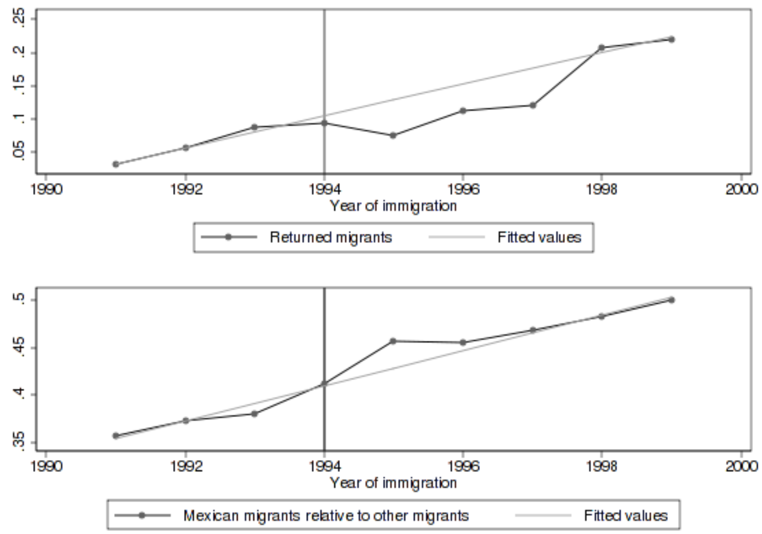
This gives me the top panel of Figure 1.

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 1. 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

Figure 1: 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.

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 1).

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

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

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

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

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

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:

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

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.

5 Appendix, revisiting the Mariel Boatlift

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.

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.

5.3 Summary Statistics

Table 12 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 12. 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 12: 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).[7]

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

[7] 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.

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:

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)

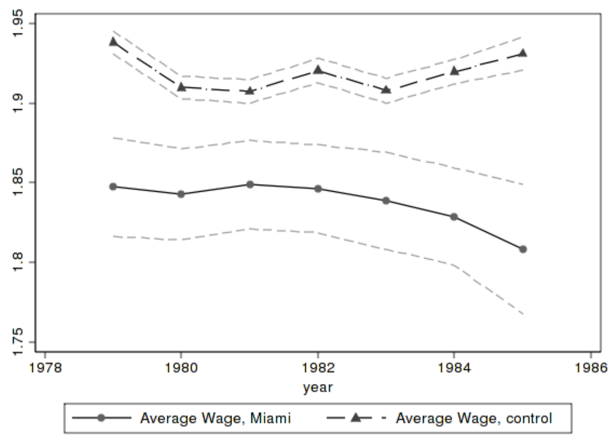
3. *uhourse*: Edited Item 25a. "How many hours per week does...USUALLY work at this job?" [1989 trough 1993 the range is 1-99.] The allocation flag for this variable is noted with the earnings variables above. For 1994 on the job is the 'main job' and the answer 'hours vary' is translated to missing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

Following the documentation in the NBER website (http://www.nber.org/morg/docs/cpsx.pdf and http://www.nber.org/morg/docs/cpsapdx.pdf) 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 2.

Figure 2: Evolution of hourly wages of white workers



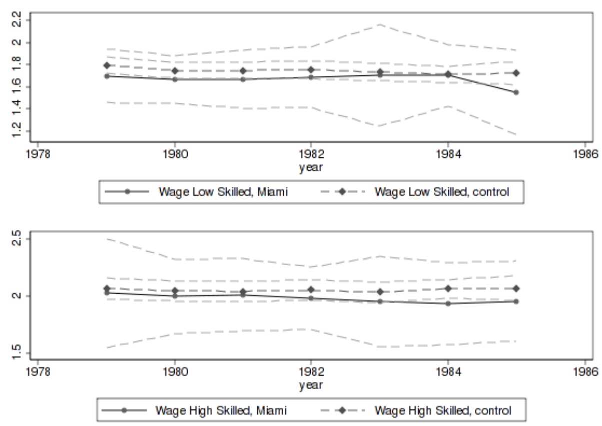
Note: CPS MORG data. This graph shows the hourly wage rate evolution of white workers in Miami and the control group of four cities: Tampa, Los Angeles, Houston and Atlanta. Dashed lines indicate the standard error of the computed average wage.

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

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 3: 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.

Figure 3 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.

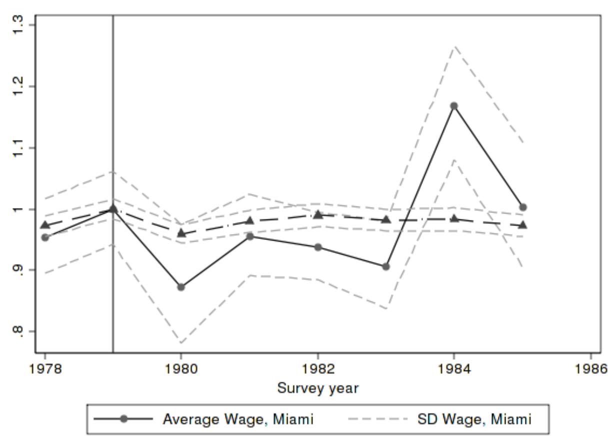
Result 4. *When distinguishing between high and low skilled workers in CPS MORG data there is little evidence that the Mariel boatlift affected wages.*

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

Figure 4: Evolution of weekly wages of white workers



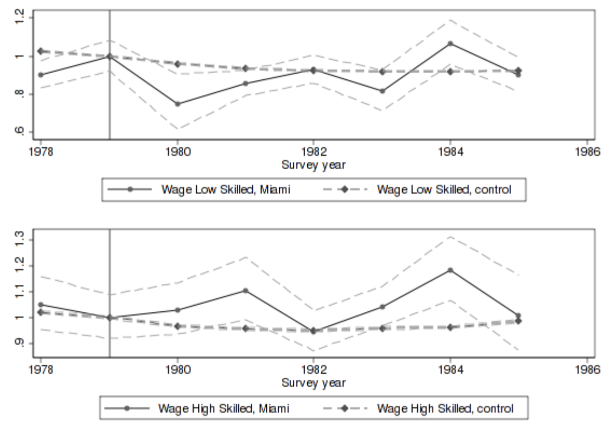
Note: March CPS data. This graph shows the wage evolution of white workers in Miami and the control group of four cities: Tampa, Los Angeles, Houston and Atlanta. Dashed lines indicate the standard error of the computed average wage. Weekly wages are computed for full year workers using yearly income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

In Figure 4 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 5.

Figure 5 shows that the drop in wages shown in Figure 4 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

Figure 5: 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.

implied labor demand elasticity for low skilled workers from these raw estimates would not be far from 1, as found in Monras (2013).

Result 5. *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.*

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:

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

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 13-15 show the exercise for 1978-1981. Every table has the same structure but different periods lengths. In Table 13 I include only 1979 and 1980. In Table 14 I include an extra pre-shock year, while in Table 15 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.

Table 13: 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				Whites	Mexican	Cuban	Black	Other
	All					Hisp.			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.

The first thing we see in Table 13 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 4 and 5. 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 14: 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 15: 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.

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