Immigration, Internal Migration, and Technology Adoption

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Abstract

An abundance of a certain factor type may encourage firms to adopt production techniques geared towards this factor. Traditional approaches have used proxies of local technology adoption in combination with exogenous changes in the local factor mix – often driven by immigrant shocks – to document this relationship. In this paper, I back-out implied technology adoption from internal migration patterns observed during the 1980s in Miami relative to a number of control groups following the Mariel Boatlift. The identifying assumption is that technology adoption explains the part of the wage recovery that cannot be explained by internal migration. Model-based estimates suggest that local technology adoption explains 50 percent and internal migration the other 50 percent of the relative wage recovery in Miami.

Key Words: International and internal migration, local shocks, local labor demand elasticity, technology adoption.

JEL Classification: F22, J20, J30

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1 Introduction

The share of immigrants has substantially increased in many OECD countries. For example, in the United States in the mid 70s under 5 percent of the population was foreign-born, while by 2010 it had increased to more than 15 percent. Perhaps more remarkably, as much as 30 percent of the high-school drop-outs in the US are currently foreign-born, while the immigrant share is under 10 percent among the middle-skilled. In fact, it is well known that immigrants in the US concentrate among workers with very low and very high levels of education (Borjas, 2003; Ottaviano and Peri, 2012). To the extend that workers with different education levels are different factors of production (Katz and Murphy, 1992), one view about immigration is that is has dramatically changed the factor mix available in OECD economies.

As Acemoglu (2002) explains, the factor mix available in an economy may affect technology or capital adoption. An abundance of one factor, say low-skilled workers, may encourage firms to adopt technologies or capital that enhances either low- or high-skilled workers' productivity, depending on the elasticity of substitution between these two factor types. If high- and low-skilled workers are imperfect substitutes, as is often estimated, an increase in the number of low-skilled workers may lead the economy to adopt low-skill biased technologies or to employ less capital that substitutes low-skilled labor. This is important because technology or capital adoption is likely to have consequences for the returns paid to each factor of production. For example, technology adoption may explain some of the results in prior literature suggesting that immigration has had small effects on wages. Hence, an important question in the economics of immigration is to understand how immigrants shape technology and capital adoption.

One way to address this question is to use a measure of technology or capital adoption and relate it to immigration. For example, Lewis (2012) uses the Census of Manufactures to assess whether plants facing immigrant-driven increases in the number of high-school dropouts adopt fewer machines per worker. His estimates suggest that a 1 percentage point increase in the fraction of high-school dropouts hired in a plant leads to a decline in plant-level machinery adoption of about 6 percent. Similarly, Clemens et al. (2018) explain the lack of employment gains for natives when the Bracero program was removed by the patterns of technology adoption in response to immigrant shocks. As explained in Lewis (2012) and Lewis (2013), the adoption of forms of capital that substitute low-skilled labor tends to attenuate the effect that immigrant-driven changes in the skill mix have on the returns to relative skills.[1]

Several issues complicate the analysis. First, there may be endogeneity between immigrant location choices and technology adoption. It is likely that immigrants choose to live in places that are developing technologies that are well suited for their skills. While previous literature has used Card (2001)-type instrumental strategies, recent papers have suggested that serial correlation may undermine this approach (Jaeger et al., 2018). Second, it is sometimes hard to measure technology or capital adoption. Previous papers have measured it as machinery or other forms of capital, like PCs per capita (Beaudry et al., 2010), but any such measure is likely to be just one aspect of the many that determine the technologies adopted in production. Data on capital adoption are also often elusive at the local level and at high frequencies.[2]

[1] Another way in which immigrant-induced changes in factor mix can be absorbed in the long-run is in the context of multisector economies. In open economy models, it is sufficient to expand the sectors using more intensively the type of labor brought by immigrant inflows. These type of models require intense across sector relocations which are typically not found in the data both in the US and in other countries, and also when firms are used instead of sectors. See for example the pioneering work by Hanson and Slaughter (2002) and Lewis (2003), and the papers by Dustmann and Glitz (2015) and Gonzalez and Ortega (2010).

[2] As far as I am aware, yearly measures of capital are only available at the state level. At the metropolitan area level

In this paper, I shed new light on the relative importance of technology adoption and internal migration in helping to dissipate (international) immigrant shocks through the lenses of an open city spatial equilibrium model (Roback, 1982; Rosen, 1974) and new empirical evidence using variation from the Mariel Boatlift episode – which exogenously increased the number of low-skilled workers in Miami by 1980. In the first part of the paper, I first document that wages in Miami declined relative to a number of control groups in the first few years after the shock, as has been shown in previous literature, but that by 1990 wage changes in Miami were similar to the rest of the US during the decade – not always emphasized in previous papers. Hence, over longer time horizons, I show that wages in Miami of *all types* of workers were similar to those in the rest of the country, despite the large inflow of low-skilled immigrants at the beginning of the decade and the evidence pointing at short-run low-skilled workers' wage declines.

Second, I document that while the share of low-skilled workers increased one to one with the inflow of Cuban immigrants in the early 1980s, by the end of the decade it had increased by only .6 low-skilled workers for each low-skilled Cuban immigrant. More precisely, I document that the share of low-skilled workers increased on impact with the Mariel shock, stayed high until 1985, and then declined until 1990 although it remained higher than it was in 1980. The beginning of the decline in the share of low-skilled workers living in Miami coincides with the period when short-run wage effects are estimated to be larger, suggesting that internal migration might have contributed to the dissipation of wage effects. This is the first paper that systematically documents the internal migration response that followed the Mariel Boatlift.

In the second part of the paper, I interpret these findings through the lenses of a spatial equilibrium model, which I then use to evaluate the relative role of local technology adoption and of internal migration in dissipating the shock. If the different local labor markets in the US are well described by the Rosen-Roback spatial equilibrium model, then when there is an immigrant-driven labor supply shock into a local labor market, for example Miami, there should be mechanisms that accommodate the shock so that (perhaps after some time) wages in Miami return to their pre-shock levels. In principle there could be many mechanisms that help to absorb labor supply shocks. First, internal migration could react to the immigrant shock, as I document and as was suggested by David Card in the conclusion to his landmark study (Card, 1990). Second, given that the labor supply shock was predominantly low-skilled, perhaps Miami specialized in traded goods that used low-skilled labor more intensively, leaving Miami inside the factor price equalization set as suggested by the Hecksher - Ohlin model of international trade (Hanson and Slaughter, 2002). Third, perhaps local technologies and capital adapted so that in the end wages of low-skilled labor remained unchanged.

While hard to separately identify the relative importance of these different channels, I argue that I can recover the relative importance of internal migration and of all other mechanisms combined – which to simplify I label as local technology adoption – from model assumptions and the estimates that I provide in the first part of the paper.[3] For this exercise, all I need is a) an estimate of the short-run local labor demand elasticity and b) an estimate of internal migration over a period of time that is sufficiently large so that potential short-run wage effects have already disappeared. Given the empirical estimates that show that wage effects have dissipated by 1990, all I need is, then an estimate of internal migration over the

data exists only for a selected number of years.

[3]I show in the model that this includes adding capital-skill complementarities (Lewis, 2013). In the model, I abstract from multi-sector open economy adjustments which can be justified by the lack evidence on massive cross-industry mobility as would be implied by the Rybczynski theorem.

entire decade, i.e. the aforementioned .6 extra low-skilled workers in 1990 for each low-skilled immigrant. The intuition behind the exercise is simple. If during the whole decade we see a lot of internal migration then local technology was perhaps not very important in dissipating wage shocks. If instead we see little internal migration and yet wages recover pre-shock levels then the role of technology adoption is likely to be much more important. Introducing this idea in an open city spatial equilibrium model and showing how to use it to back out technological change is arguably the second contribution of this paper.

Through the lenses of the model, I estimate that technology adoption biased towards the skills of the Cuban inflows explains around 50 percent of the wage recovery, while the other 50 percent is explained by internal migration. More generally, given the discussion in previous literature on the wage estimates arising from the Mariel Boatlift episode (Borjas, 2017; Card, 1990; Clemens and Hunt, 2018; Peri and Yasenov, 2019), I provide a range of model-based estimates of this decomposition as a function of the local labor demand elasticity and potential migration responses. Alternative estimates suggest that, if anything, internal migration is perhaps relatively more important than technology adoption.

This paper is closely related to some of my previous work, most prominently Monras (Forthcoming). In Monras (Forthcoming), I use the Mexican Peso crisis of 1995 to estimate a dynamic spatial equilibrium model with many locations. Using the estimated model I study the counterfactual evolution of wages under different assumptions on technology adoption. Relative to Monras (Forthcoming), in this paper I adapt and simplify the conceptual framework to the small open economy case of Miami and use variation from the most well studied immigrant-driven supply shock. This hopefully offers a new perspective on what we learn from the Mariel Boatlift.

As mentioned before, this paper is related to the papers that investigate the link between technology adoption and immigrant shocks (Cascio and Lewis, 2018; Clemens et al., 2018; Lafortune et al., Forthcoming, 2015; Lewis, 2012). Relative to these papers, I offer a model-based measure of the role that technology adoption plays in dissipating the wage effects of immigrant-driven labor supply shocks using data from the Mariel Boatlift episode. The evidence I present complements this body of prior work. An important difference is that this previous work focuses on how technology or capital adoption can reduce the effect of immigrant shocks on *relative* factor rewards. Instead in this paper, I use the spatial equilibrium assumption to back out how technology adoption may mitigate the effects of immigration on the *level* of wages.

This paper is also related to the work that has discussed the internal migration responses to immigrant shocks. Borjas et al. (1997) argue that the small estimated effects of immigrant shocks across metropolitan areas may be related to internal migration. Card and DiNardo (2000) show that on average internal migration responses to immigrant shocks are small. Peri and Sparber (2011) corroborate this evidence by defending Card and DiNardo (2000) empirical strategy in contraposition to Borjas (2006). In a recent paper (Albert and Monras, 2020), we argue that the reason why previous literature has found limited evidence for internal migration responses to local shocks is related to two facts. On the one hand, immigrant shocks tend to occur in expensive locations, where, as we show, it is easy for natives to respond by relocating. On the other hand, the immigrant networks instrument tends to put weight on small metropolitan areas close to the Mexican border hence resulting in lower internal mobility estimates than when using other identification strategies. In all, Albert and Monras (2020) show that natives relocate in response to immigrant flows, something that I also find in this paper using variation from the Mariel Boatlift.

Finally, this paper is related to the large literature on the Mariel Boatlift. 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 differential effect of Cuban immigrants on wages.[4] It is hard to emphasize the importance that this study has had in shaping our thinking about immigration, and more broadly, about using natural experiments in economics. However, Borjas (2017) posed an important challenge to what we had learnt from the Mariel Boatlift episode. Two main things differentiate Borjas' analysis from the original Card (1990). First, he concentrates on studying the wage dynamics of native male workers in Miami in the lowest education group. Second, Borjas (2017) criticizes the control group of cities used in Card (1990) mainly on the grounds that Card chose the control group based on employment trends that included some of the years post-Mariel shock. The conclusion in Borjas (2017) seems to be radically different than in Card (1990). Whereas the initial analysis emphasized that native workers in Miami were not affected by the immigrant shock relative to workers in the control group, Borjas (2017) concludes that there is at least one group of workers that was severely affected. Wage declines for this group are estimated to be as large as 30 percent.

Since Borjas' reappraisal, several papers have investigated the episode in detail. The debate has been over two different issues. On the one hand, the micro-level number of observations of male high-school dropouts which are used to compute wage trends is small, in many occasions below 30 individual observations. This means that average wages are not computed with much precision and hence, small changes in the sample of workers used to compute these average wages may have substantial effects on the point estimates. This has been, at least in part, the critique emphasized in Peri and Yasenov (2019) and Clemens and Hunt (2018). On the other hand, there has been some debate over what is the best possible control group of cities (Peri and Yasenov, 2019). The pool of potential control cities is not large, since in the early 1980s there are only 38 metropolitan areas that are covered by the March supplements of the Current Population Survey (CPS) data. Hence, small changes on the metropolitan areas that are used as a control group also lead to large changes in point estimates. None of these previous papers, however, looks at internal migration and technology adoption using the Mariel Boatlift episode. In this paper, I try to take into account the diversity of estimates by showing how the results change when deviating from my baseline estimates rather than taking a stance on what is the best estimate in the literature.

In what follows I first present the empirical evidence in Section 2. In Section 3, I introduce the model and in Section 4 I use the model to back out the implied technology adoption and its relative role in dissipating wage effects over the decade of the 1980s.

2 Empirical evidence

2.1 Data

In this paper I use standard sources of publicly available data. To analyze the short-run effects of the Mariel Boatlift episode I use the March supplements and the outgoing rotation group files of the CPS. The March supplements of the CPS have complete information on wage income during the year prior to the interview and weeks worked, which allows to construct weekly wages. It also contains information on the education level of the individuals in the sample. In particular I can construct 4 education codes:

[4] Card distinguishes by racial groups and quartiles in the wage distribution but not by education groups.

high-school drop-outs, high-school graduates, some college, and college graduates or more. These four groups split the labor market of 1980 in roughly four equally sized groups.

To compute wages I use the exact same sample as Borjas (2017). In particular, I restrict the sample to non-Hispanic prime-age, i.e. 25 to 59 years old, working males. During the 80s women were fast entering the labor market. Hence, when using women to compute wage trends it may be that wage changes are driven by changes in the composition of workers from year to year. This is why I prefer to use only male workers. Including women in the regressions leads to similar results, although substantially more noisy. Arguably we would like to exclude foreign-born individuals if the object of interest is native wages. Birth place is not recorded in the CPS data until 1994, and hence the best approximation is the Hispanic variable, which allows to identify Hispanics of Cuban and of Mexican origin.

An alternative data set to compute wages during this period is the outgoing rotation group files of the CPS. I apply the exact same sample selection when using these data. The number of pre-shock years available in the CPS ORG files is only 1979 and 1980 (which is driven by the coverage of metropolitan areas), whereas the pre-shock years when using the March CPS data include 1975 to 1980.

To study internal migration I simply look at the share of workers of a certain characteristic that live in Miami. This share could change for reasons other than internal migration. For instance, it could be that mortality rates for say, high-school drop-outs were higher in Miami than in other cities, leading to a decrease in the share of low-skilled workers in Miami. Alternatively, it could be that international migration from places other than Cuba is driving this relative share. From the view point of the model, it does not matter what is driving the change in the composition of workers in Miami. Hence, labeling all worker movements as internal migration is just one way to speak to changes in the relative supply of workers across metropolitan areas. When documenting internal migration I rely on the March CPS data.

To estimate longer-run effects on wages and internal migration, I use the Censuses of 1980 and 1990, provided by Ruggles et al. (2016). From these censuses I can construct weekly wages in 1980 and 1990, following the sample selection applied to the CPS data. I can also obtain a measure of the the size of the Mariel shock. For that I follow Borjas and Monras (2017). In particular, I use data from the 1990 Census on Cuban immigrants arriving in 1980 and 1981 (since these two years are grouped into a single category), which were residing in Miami in 1985, to estimate the number of Cuban migrants that moved to Miami during the Mariel Boatlift. The assumption is that Cubans observed in Miami in 1985 are unlikely to have changed residence during the first five years of the decade and hence represent a good proxy for the size of the shock. If anything we can imagine that the shock was larger than estimated with the 1990 Census data. The Census data allows me to compute the relative size of the shock for each education group, since the Census in 1990 records the educational attainment of the Cuban immigrants. Summary stats tables for these data are provided in Borjas (2017) and Borjas and Monras (2017).

2.2 Identification

In what follows, I run two types of regressions. On the one hand, I use the Mariel Boatlift shock in a standard difference in difference setting. The key identification assumption in this case will be that Miami would have followed a similar trend than that followed by the control group. Difference in difference specifications are quite standard. I use graphical representations of the treatment dummy in each year to analyse the trends in Miami, and in Miami relative to various control groups. I follow (Card, 1990) and Borjas (2017) in using two alternative sets of metropolitan areas to construct the control group.

I define as the Card control group the metropolitan areas used as control in the initial Card study: Atlanta, Houston, Los Angeles, and Tampa. Borjas proposed an alternative group of metropolitan areas: Anaheim, Rochester, Nassau-Suffolk, and San Jose. I also report results comparing Miami to all the other identifiable metropolitan areas (38).

On the other hand, I use specifications where I leverage the intensity of the treatment, i.e. where I focus on Cuban-induced increases in the working force of specific factor types of different intensity. To allocate Cuban-induced migration across labor markets I use the standard networks instrument. The key identification assumption is that the reasons that brought earlier Cuban immigrant to locate in places like Miami are unrelated to contemporaneous ones.

More specifically, I estimate equations of the following type:

$$\Delta \ln y_{ce} = \alpha + \beta \frac{\text{Cub}_{ce}}{\text{Nat}_{ce}} + \delta_c + \delta_e + \varepsilon_{ce} \tag{1}$$

Where c indexes metropolitan areas and e indexes the four education groups: high-school drop-outs, high-school graduates, some college, and college graduates or more. δ_c and δ_e are metropolitan area and education fixed effects, respectively.

As it is well known, this equation identifies the effect of immigrant shocks on outcomes of interest if immigrant location patterns are uncorrelated to the error term. In practice, this is unlikely to be the case. There may be unobserved local labor demand shocks that drive immigrants and improve outcomes of interest like wages. Hence, the need for an instrument.

In this paper I use an instrument inspired in the standard networks instrument used in the literature. The fist stage regression can be expressed as follows:

$$\frac{\text{Cub}_{ce}}{\text{Nat}_{ce}} = \alpha + \beta \frac{\text{Cub}_{ce,0}}{\text{Nat}_{ce,0}} + \delta_c + \delta_e + \varepsilon_{ce} \tag{2}$$

where Cub_{ce} is the inflow of Cuban workers that arrived in each metropolitan area during the Mariel Boatlift episode with education level e and natives is the size of the local labor force excluding Cuban workers.[5]

The most standard way to use the immigrant networks IV is to assign the flow of immigrants from each country of origin according to the initial distribution of immigrants across metropolitan areas. As argued in (Goldsmith-Pinkham et al., 2018), in this setting identification mostly comes from the "shares". A more direct way to use the identifying variation is to directly predict the inflow by the initial share: $\frac{\text{Cub}_{ce,0}}{\text{Nat}_{ce,0}}$. This variable is the size of the Cuban stock relative to the local population at the initial period, in this case 1980, i.e. before the Mariel Boatlift. This variable captures an intensity of treatment, i.e. it measures how important are Cubans (relative to natives) in each metropolitan area-education cell.

If the initial importance of Cubans across cells is uncorrelated with current changes in outcomes of interest then this identification strategy identifies the causal effect of actual Cuban inflows on the variables of interest. Running this regression in the period of the Mariel Boatlift ensures that Cuban inflows are generated by a push, rather than a pull, factor, and hence unlikely to be related to developments in the US economy.

[5] I identify Mariel immigrants as those immigrants arriving to the US in 1981-1983 Census category, as reported in the 1990 Census. I also identify in the 1990 Census the location of each individual in 1985, which I take as a proxy of the location of arrival. Note that this specidication, as explained in Borjas and Monras (2017) can be obtained directly from a representative firm like the one I introduce in Section 3.

2.3 Short-run estimates

On April 20, 1980, Fidel Castro declared that Cuban nationals could emigrate freely from the port of Mariel. Around 125,000 Cubans took this opportunity and migrated towards the United States during the period that goes from April 23rd to the month of October of 1980. Nearly 70,000 immigrants likely settled in Miami, something that accounts for around 8 percent of the workforce of Miami at the time. Cuban immigrants were very low-skilled. As much as 62 percent lacked a high-school diploma compared to around 23 percent among the natives. Hence, these low-skilled workers experienced a labor supply shock of around 32 percent of the workforce prior to the shock (Borjas and Monras, 2017).

I start the analysis of the Mariel Boatlift episode by analyzing what happened to wages and to the share of low-skilled workers in Miami over the 1980s. This replicates and extends the results reported in Borjas (2017).

To study how wages of low-skilled workers changed in Miami with the Mariel Boatlift I first use a simple difference-in-difference specification:

$$\ln w_{i,c,t} = \delta_c + \delta_t + \beta \text{Post Mariel}_t \text{ x Miami}_c + \gamma X_{i,c,t} + \varepsilon_{i,c,t} \quad (3)$$

where $\ln w_{i,c,t}$ is the wage of worker i in city c at time t, Post Mariel_t is a dummy variable that takes value one after 1980, Miami_c is a dummy variable that takes value one for Miami, and where δ_c and δ_t are city and time fixed effects respectively. I run this regression using only high-school drop-outs. $X_{i,c,t}$ are individual level controls.

Note that I can use in equation 3 an interaction of the time fixed effects with the dummy for Miami, instead of Post Mariel_t x Miami_c, to plot exactly where the estimate of β comes from. Figure 2 shows this exercise.

Equation 3 captures the causal effect of immigration on wages in the short-run as long as the control group is comparable to the treated group. In the particular case of Miami, we have only one treated location and hence inference is complicated from the fact that there may be serial correlation in outcome variables and that we only have one treated location and at most 38 control cities (which is the number of cities available in the CPS data). I report robust standard errors that allow for heteroskedasticity.[6]

The results are reported in Panel A of Figure 2. I report estimates for Miami, in an event-type setting and estimates for Miami relative to three different control groups: the original Card control group – Atlanta, Houston, LA, and Tampa –, the control group proposed in Borjas (2017) – Anaheim, Nasssau, Rochester, and San Jose–, and a control group that includes all the metropolitan areas in the US for which we have data in the early 1980s.

Figure 2 goes around here

Irrespective of the control group that I use, Figure 2 shows that there are no systematic trends in the wage evolution in Miami leading to the arrival of the Mariel Boatlift immigrants. Wage declines are small in the first two years after the shock and significantly decrease thereafter. The largest impact is

[6] In the regressions where I use all the metropolitan areas I can also control for serial correlation by clustering standard errors at the metropolitan area level. When I do so, standard errors are in general smaller. I obtain similar estimates of the standard errors when I compute bootstrapped standard errors. Stata does not allow to use statistical weights when computing bootstrapped standard errors, which is why I prefer to report robust standard errors.

around 1985 or 1986. After this, wages recover so that by 1990 there is no differential impact in Miami relative to the various control locations. There are many reasons that may explain why wages did not react on impact, but rather after one or two years. It could be that local technologies adapted to the shock, although this alone has a hard time explaining the later decline. It could also be that there is some wage stickiness, so that wage effects are only observable when new contracts are negotiated. A final explanation could be that it took a couple of years for the Mariel immigrants to enter Miami's labor market, perhaps because they needed to learn English or other specific skills. Whatever the reasons, it seems that there is a decline in wages of the least skilled workers in Miami which may be related to the unexpectedly large flow of immigrants during these years. As explained in Borjas and Monras (2017) the wage decline is only observed for the least skilled native workers. In fact, labor market outcomes of more skilled workers in Miami improved relative to the control groups.

Panels A and B of Table 1 quantify the wage effects using a number of alternative specifications that follow equation 3. In the first column of Panel A, I estimate the wage effects of the Mariel Boatlift using all other 37 metropolitan areas as control group. The second column uses only the Card control and column 3 uses the Borjas control. I repeat the estimates in columns 4, 5, and 6 but adding individual level controls (most importantly a dummy for African American workers which is important given Clemens and Hunt (2018) finding that there seems to be a change in the composition in the CPS sample around 1985). All the estimates suggest that wages were lower in Miami in the aftermath of the labor supply shock, i.e. between 1981 and 1985, than in the control group. In Panel B, I report the exact same regressions as in Panel A but using CPS ORG data. The results are similar, although smaller, as has been pointed already in the literature.

In panel C, I report the estimates using the intensity of treatment as explained in Section 2.2, where the difference in wages is taken between the pre-years 1977-1979, and the post years 1981-1984. The first two columns report the first stage regression. In column 1 without controls, while in column 2 I control for the change of native population which controls for short-run internal migration. It is clear from these columns that the inflow of Cuban migrants was most important in metropolitan-skill cells where Cubans were already a large share. Controlling for native internal migration does not change this result, since, as I document more precisely below, the internal migration response does not start until later in the period. Columns 3 and 4 report the OLS estimates. The point estimate is around -1.3. This is a direct estimate of the inverse of the local labor demand elasticity which I use later in the model. The IV estimates are very similar to the OLS estimates. This is so, because both the initial share of Cuban immigrants and the new inflows concentrate among high-school drop-outs in Miami. This estimate implies that an increase in a metropolitan area-skill cell equivalent to 10 percent of the native workforce in that cell reduces wages by 13 percent on impact.

Table 1 goes around here

The recovery of wages that starts in Miami around 1985 or 1986 coincides in time with the decrease in the share of low-skilled workers living in Miami relative to the control groups. To investigate this I use the following regression framework:

$$\text{In Miami}_{i,t} = \delta_c + \beta_1 \text{Years 1981 - 1984}_t + \beta_2 \text{Years 1985 - 1990}_t + \varepsilon_{i,t} \quad (4)$$

where In Miami$_{i,t}$ is a variable that takes value one if individual i is in Miami at time t, Years 1981 - 1984$_t$ is a dummy variable that takes value one for the years 1981 - 1984, and Years 1985 - 1990$_t$ is a dummy variable that takes value one for the years 1985 - 1990. I run this regression using all high-school drop-out workers in Miami and in the control group over the period 1977 to 1990. Hence, β_i captures the share of low-skilled workers in Miami relative to the omitted time period (1977-1980), relative to the control group. I can estimate β_i using various types of estimators. I can for example run simple OLS, which would give linear probability model estimates, or I can estimate probit models. The results do not change. I use in what follows probit models. Finally, note that, as before, I can in fact plot an estimate for each of the years in the regression.

To gain intuition on the estimates I first plot the estimate for each of the years in the sample. In Panel B of Figure 2 we see that the share of low-skilled workers living in Miami increases in 1980 coinciding exactly with the arrival of the Mariel Boatlift Cuban immigrants. This is so, both when we compare Miami to rest of the US, to Card or Borjas' placebos, or when we compare it to all the metropolitan areas in the South Atlantic region.

A second remarkable aspect shown in panel B of Figure 2 is that the relative concentration of low-skilled workers in Miami only seems to last until 1984 or 1985. After that, it seems to decline. Depending on the control group, the decline seems to be complete or it seems that there is a small decline and by the end of the decade there are still more low-skilled workers in Miami than in the control cities.

Table 2 quantifies what we see in Panel B of Figure 2. Panel A of Table 1 shows that there is a sharp increase in the share of low-skilled workers in Miami, which somewhat disappears by the end of the decade. In this table, unlike in the figure, I control for observable characteristics. When comparing Miami to the rest of the US, we see that Miami gained low-skilled workers in the period 1981 to 1984 and then lost some of these workers. In the period 1985 to 1990, however, Miami retained roughly two thirds of the low-skilled workers gained in the early 80s when compared to all of the US. Panel B of Table 1 repeats the exercise but only for high-skilled workers. It is quite clear from this panel that the increased concentration in Miami only affected low-skilled workers.

Table 2 goes around here

2.4 Long-run estimates

To check that indeed wages of low-skilled workers are back to "normal" by 1990 as appreciated in Figure 2, I use the following regression:

$$\Delta \ln w_{ce} = \alpha + \beta \frac{\text{Cub}_{ce}}{\text{Nat}_{ce}} + \delta_c + \delta_e + \varepsilon_{ce} \tag{5}$$

where $\Delta \ln w_{ce}$ is the change in wages of workers of education e between 1980 and 1990 in metropolitan area c, and where $\frac{\text{Cub}_{ce}}{\text{Nat}_{ce}}$ is the Mariel Boatlift induced shock to labor supply in each city and education group, which is measured as the number of Cubans that in the 1990 reported to be living in each city in 1985 and who claim to have arrived in the US in 1980-1981 with education e, divided by the number of non-Cuban workers in each city and education group in 1985. δ_c and δ_e are city and education fixed effects. These allow for city specific and (national) education specific time trends. In some specifications

I restrict the regression to low-skilled workers. In this case I cannot include city and education fixed effects.

To control for the possible endogenous location choice of immigrants I instrument $\frac{\text{Cub}_{ce}}{\text{Nat}_{ce}}$ by the share of Cubans in each city before the Mariel Boatlift shock as explained in Section 2.2.

It is worth noting that running this regression between Censuses means that β can be interpreted as the inverse local labor demand elasticity adjusted for internal migration. This is, in the short run, before any adjustment takes place, β is the (inverse) local labor demand elasticity. If there are adjustments, then β contains also these adjustments. I discuss this point in more detail in Section 3.

Table 3 goes around here

Table 3 reports these results. In the first column I show that the initial share of Cubans (among high-school drop-outs) is a good predictor of the inflow of Cubans during the Mariel Boatlift episode across metropolitan areas. The same is true if I expand the regression to include the four education groups and I include metropolitan area and education fixed effects. In columns 3 and 4, I estimate the wage effects over the entire decade using OLS regressions. It is clear from these two columns that wages of low skilled workers in high-Cuban locations do not seem to be lower than in lower Cuban migration locations. The same is true when including variation by education group in column 4. In column 5 and 6, I report IV estimates of the long-run effect of the Mariel Boatlift on native wages. Both when using variation across cities for high-school drop-outs or when using all four education groups, it is clear that over a 10 year gap horizon, Cuban immigrants from the Mariel Boatlift do not seem to have affected low-skilled workers wages, or, for that matter, wages of other factor types within metropolitan areas.

To investigate how much internal migration there was during the decade I use the following specification:

$$\Delta \text{Share of low-skilled}_c = \alpha + (1-\lambda)\frac{\text{Cub}_c}{\text{Nat}_c} + \varepsilon_c \tag{6}$$

where Share of low-skilled$_c$ is the number of low-skilled workers as a fraction of the total population, and where the change is taken between 1980 and 1990. In this case, an estimate of $\lambda = 0$ indicates that there is no internal migration. This is, for each Cuban low-skilled immigrant we have that the share of low-skilled workers increases by exactly 1. Instead if $\lambda = 1$ then it means that internal migration completely dissipates the local shock, so that Miami, by 1990 does not have more low-skilled workers despite the sizable unexpected inflow of Cuban low-skilled workers.

Results of regression 6 are shown in Table 3, in columns 3 and 4. Both with the simple OLS and with the IV, I obtain estimates of around .6, i.e $\hat{\lambda} = 0.4$. This means that there was some internal migration but that Miami gained low-skilled workers relative to the other cities in the US.

3 Model

In this section I introduce an "open city" spatial equilibrium model of a local labor market (think of Miami). It is "open city" because it is a model of just one city that is small relative to the rest of the aggregate economy, hence if workers in Miami leave the city, they are small in numbers relative to workers outside Miami so that they have negligible effects. The model is a spatial equilibrium model in the sense that there is an outside level of utility that workers in Miami can attain if they migrate to another US city.

3.1 Indirect utility

Indirect utility is derived from assuming that individuals consume all their income in one good and value the level of amenities that the location offers (A). Assuming that the price of the final good is the numeraire we obtain that:

$$\ln V = \ln A + \ln w \tag{7}$$

Workers can either live in this local labor market and obtain indirect utility $\ln V$ or move elsewhere and obtain $\bar{u}$ instead. Miami is small relative to the rest of the economy in the sense that no matter how many workers leave Miami or move towards Miami, $\bar{u}$ is unaffected. Note also, that since workers do not have a dis-utility from working they supply inelastically their labor endowment.

3.2 Local labor market

The local labor market is defined by the local production function of a representative, perfectly competitive firm, given by:

$$Y = AF(H, L, K_M) = A(\tilde{A}^H(H)^{\frac{\sigma-1}{\sigma}} + \tilde{A}^L(L + \gamma\sigma K_M)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{8}$$

where Y denotes total output, A denotes Hicks-neutral technology, $\tilde{A}^H$ and $\tilde{A}^L$ denote the weights in production or skill-biased technologies of high- (H) and low-skilled workers (L) respectively and σ is the elasticity of substitution between high- and low-skilled workers. K_M represents capital that can substitute low-skilled labor. This captures the capital-skill complementarity emphasized in prior literature and allows me to discuss the potentially different role of pure technology adoption (i.e. changes in $\tilde{A}_L$) from non-Hicks neutral capital adoption.[7]

The representative firm maximizes profits taking factor prices w^L and w^H as given:

$$\max AF(H, L) - w^L L - w^H H - rK_M$$

From the profit maximization problem we obtain the demand for labor. This is given by:

$$\ln w^L \approx \ln A + \ln \tilde{A}^L - \frac{1}{\sigma}\ln L + \frac{1}{\sigma}\ln Y - \gamma k_M \tag{9}$$

This equation simply relates wages for one factor type, in this case low-skilled workers to Hicks neutral technology (A), the technological weight of low-skilled workers in the local production (A^L), the total number of low-skilled workers (L), total output (Y), and capital per (low-skilled) workers (k_M). It is worth noting that capital adoption and technology adoption are, in this model, very similar. One can re-label $\tilde{A}_l$ to incorporate k_M: $\ln A^L = \ln \tilde{A}^L - \gamma k_M$. The most important conceptual difference is that

[7] Lewis (2013) allows for potentially imperfect substitutability between low-skilled labor and capital. I present a simpler production function. However, the main points I discuss below extend to the imperfect substitutability case as long as capital and high-skilled labor are q complements.

one could model the supply of capital to obtain closed form solutions on how much this mechanism for absorption of low-skilled labor matters. I abstract in what follows from explicitly quantifying the importance (or the reduction in) of capital adoption that substitutes low-skilled labor (which is akin to assuming $\gamma = 0$).

Note also that hicks-neutral technological change could help wages of a particular factor return to its initial level. In this case, though, rewards to other factors, like high-skilled workers wages would also increase, driving high-skilled people into the economy, which is not observed in the data, as documented in Table 2, Panel B. Moreover, changes in A alone would not change relative wages following an exogenous inflow of low-skilled immigrant workers in the longer-run, as explained in Lewis (2013). In other words, in that case the effect of the short-run immigrant shock on *relative* factor rewards would be the same as the longer run one. This is not what the data suggests, as can be seen in Panel C of Table 1 and columns 5 and 6 of Table 3. This is why I abstract in what follows from Hicks-neutral technological change.

3.3 Wage effects

Given equation 9, it is easy to study the effect on wages of an inflow of low-skilled immigrants I. For this we can compute the derivative of wages with respect to immigration which is given by the following equation:[8]

$$\frac{\partial \ln w^L}{\partial \ln I} = \nu\pi - \frac{1}{\sigma}(1-\Gamma)\pi\lambda \tag{10}$$

where $0 < \Gamma = (\frac{L}{Y})^{\frac{\sigma-1}{\sigma}} < 1$ is essentially the share of low-skilled workers in final production, $\nu = \frac{\partial \ln A_L}{\partial \ln L} = \frac{\partial \ln A_L}{\partial \ln I}\frac{\partial \ln I}{\partial \ln L} = \frac{\partial \ln A_L}{\partial \ln I}/\pi$ is the response of local technologies (potentially including capital k_M) to low-skilled workers, $0 \leq \lambda = \frac{\partial L}{\partial I} \leq 1$ is the internal migration response, and $0 < \pi = \frac{I}{L} < 1$ is the share of immigrants in the economy.

Note that this equation is saying that the effect of an immigrant shock on wages depends on how local technologies and internal migration respond (mediated by the shape of the local labor demand elasticity). In particular, we can easily show that $\frac{\partial \ln w^L}{\partial \ln I} < 0$ if and only if $\nu < \frac{(1-\Gamma)}{\sigma}\lambda$, i.e. wages decrease with an immigrant shock unless local technologies change or internal migration dissipate these wage effects.

To gain some more intuition, if technologies do not adapt, so that $\nu = 0$, we have that wage effects are given by $-\frac{1}{\sigma}(1-\Gamma)\pi\lambda$ and hence, are negative as long as $\lambda > 0$. If instead $\lambda = 0$ then it means that internal migration completely dissipates the shock. If there is no internal migration, i.e. $\lambda = 1$, then there are negative wage effects on impact as long as local technologies do not adapt sufficiently (fast), i.e. as long as $\nu < \frac{(1-\Gamma)}{\sigma}$.

3.4 Short-run

I define the short-run as a sufficiently short period of time so that there is no time for internal migration and no time for technology adoption. I.e. a time when $\lambda = 1$ and $\nu = 0$. In this case, the wage equation becomes:

$$\frac{\partial \ln w^L}{\partial \pi} = -\frac{1}{\sigma}(1-\Gamma)$$

[8] For simplicity I assume that natives and immigrants are perfect substitutes. This framework can be expanded to the case of imperfect substitutability between natives and immigrants.

Or if we want to use the relative demand for low- to high-skilled workers:

$$\frac{\partial \ln(w^L/w^H)}{\partial \pi} = -\frac{1}{\sigma} \tag{11}$$

And hence, under the assumption that local technologies do no adapt in the very short-run we can use equation 11 to estimate σ. Note that we can obtain $-\frac{1}{\sigma}(1-\Gamma)$ from the regressions shown in Panels A and B of Table 1 if we have an estimate of the size of the shock in Miami. If the size of the shock in Miami is equivalent to 25 percent of the low-skilled Miami labor force, then the estimate of $-\frac{1}{\sigma}(1-\Gamma)$ is equal to the estimates shown in the Table divided by .25. Hence, it is easy to see that Table 1 suggests that $-\frac{1}{\sigma}(1-\Gamma)$ is between .7 and 1. Not surprisingly we obtain a similar estimate of the inverse local labor demand elasticity when in Panel C of Table 1 I relate wage changes to the size of the inflow of Cuban workers following the Mariel Boatlift.

3.5 Long-run

In the long-run, indirect utilities are equalized across space and hence it must be the case that wage effects are exactly equal to zero.[9] In this case we have that:

$$\nu = \frac{\partial \ln A_L}{\partial \ln L} = \frac{(1-\Gamma)}{\sigma}\lambda \tag{12}$$

This equation says that in the long-run internal migration responds sufficiently so that wages recover their pre-shock level. Hence, if we have an estimate of λ, of σ and of Γ we can back out how much local technologies changed.

The interpretation of ν is very concrete. It is the increase in the long-run demand for low-skilled labor coming from an increase in the supply of workers. Hence, it is the endogenous response of the representative firm to a change in local factor endowments given the internal mobility decisions of workers.

While I have introduced an allegedly simple model, it is easy to generalize it in many dimensions. For instance, I have assumed a unique final good which I have used as the numeraire. It is perhaps the case that immigrants affect local consumption, which may affect local prices. One way to think about this would be to introduce two goods, one that is freely traded and another one that is non-tradable (like housing). Then immigrants may consume locally and hence increase the local demand for this non-tradable good. If this was the case ν would capture the reduced form effect of the combined impact of immigrants on local technology adoption and local demand. Another simplification I introduced is to assume that there are no idiosyncratic tastes for living in particular locations. Idiosyncratic tastes for living in Miami would result in some long-run wage effects which I abstract from given that my long-run estimates on wages are not statistically different than zero. Finally, it is worth mentioning that wage effects can also dissipate in a two sector model with different factor intensity usage across sectors. In this case, technology adoption is equivalent to the movement of workers to the right sector of specialization. From a city level aggregate perspective, a change in local technology in a representative sector, or a change in the relative size of two sectors with different technologies is very similar (Acemoglu and Autor, 2011).

[9] This comes from the small open economy assumption, if instead we had a many location model, wages would return to a almost the same level unless Miami was a large location.

3.6 Local technology adoption and internal migration

We can use the model to think about the role that local technology adoption and internal migration play in dissipating wage effects of immigration. To do so, it is perhaps simpler to use a graph that illustrates the model. The y-axis of Figure 1 displays wages and the x-axis employment. Initially the market equilibrium is given by the intersection of the initial demand for labor (D_L^*) and the initial supply of labor (L^*). The initial market equilibrium is, thus, point A in the figure. When an unexpected immigrant supply shock hits the economy, the labor supply curve moves to the right, which in the figure is shown as L^1. Before local technologies or internal migration respond, wages drop to point B. By comparing the drop in wage from w^* to w^1 and the size of the labor supply shock ($L^1 - L^*$) we can compute the local labor demand elasticity σ.

Figure 1 goes around here

After this initial shock both local technologies and internal migration react to bring the economy back to the initial wage. This is, in the figure, point D. In the data, we can see how much internal migration responds. This is, we can estimate the difference between L^1 and L^{**}. If only internal migration was contributing to dissipating wage effects we would have that the equilibrium would be at point C_1 and hence at a level of wages below the initial one. Hence, it must be that local technologies change to make the demand for labor to move from D_L^* to D_L^{**}. This is my proposed estimate of ν. In the Figure we can see directly the effect of local technology adoption by looking at point C_2 which is the level of wages in equilibrium when internal migration is shut down.

With these computations, moreover, we can decompose the wage recovery between the contribution of internal migration and local technology adoption. This is, we can obtain the demand D_L^{**} from the estimate of ν. By evaluating wages with the immigrant shock at this level of demand we can compute the level of wages that would prevail if there was no internal migration. This is given by the wage w^2 in the figure. Then, we can compute the difference between w^* and w^1 which is the total short-run wage change, and decompose the wage recovery between moving from w^1 to w^2, which is the part explained by technology adoption and the recovery from w^2 to w^*, which is the part explained by internal migration.

4 Decomposition

With the estimates provided in Section 2, we can recover the change in the demand induced by factor-biased technology adoption implied by the model presented in Section 3. For this we only need to realize that:

$$\hat{\nu} = \frac{(1-\Gamma)}{\hat{\sigma}}\hat{\lambda}$$

where again, Γ is the share of high-school dropouts in Miami's labor force – which is a small number, around 20% in 1980 (Borjas and Monras, 2017) –, $\hat{\sigma}$ is an estimate of the local labor demand elasticity, which under the assumption that technology does not respond immediately can be estimated from the short-run wage response. In Panel C of Table 1 I estimate this parameter to be around -1. This estimate is in line with Table 1. If the labor supply shock was equivalent to .25 percent of the low-skilled labor force and wages are estimated to have declined by between 10 and 30 percent, then it means that the inverse local labor demand elasticity is between .4 and 1.2. Finally, $\hat{\lambda}$ is the long-run internal migration response, which we have estimated in Table 3 to be around .4.

With these estimates we can use Section 3.6 to decompose the role of local technology adoption and internal migration in explaining the wage recovery. I show this exercise in Table 4. The first row shows the baseline estimates. Given $\hat{\sigma}$ and $\hat{\lambda}$ obtaining $\hat{\nu}$ is simple. The baseline estimates suggest that around 50 percent of the wage recovery is explained by technology adoption and 50 percent by internal migration. In the last column of this row, I report an estimate of the internal migration elasticity. This measures how many low-skilled workers left Miami between 1985 to 1990 given the change in low-skilled wages until 1985. To obtain the change in low-skilled wages I multiply the inverse local labor demand elasticity by the size of the local shock in Miami, which was around 25 to 30 percent. To be conservative I assume that the shock was equivalent to 25 percent of the low-skilled labor market. Having this estimate is useful since it can be compared to the literature, which has estimated this number to be between 1.5 and 3 (Caliendo et al., 2015; Diamond, 2015; Monras, Forthcoming). The baseline estimates suggest that the wage and internal migration responses are consistent with an internal migration elasticity of around 1.6, i.e. inside the range of estimates in other literature.

Given the controversy surrounding the wage estimates obtained from the Mariel Boatlift episode, I investigate, in Table 4, the sensitivity of the decomposition of the wage recovery between internal migration and local technology adoption using alternative estimates. In the second row, I assume that the inverse labor demand elasticity is equal to .4. This would be in line with the low estimates in prior literature (Clemens and Hunt, 2018; Peri and Yasenov, 2019) and with the lower estimates in Table 1. Given the estimate on internal migration obtained from the Census data, an inverse local labor demand elasticity of 0.4 would imply an estimate of ν equal to around 0.2. In this case, local technology would be less important and would account for only 19 percent of the wage recovery. The reason for that is that internal migration would be very reactive. This estimate would imply an internal migration elasticity of 4, which is much higher than is estimated in other papers. Intuitively, seeing .4 low-skilled workers leaving Miami for each Cuban arrival given a small change in wages makes the migration elasticity very large.

In the third row, I assume an inverse local labor demand elasticity of 0.7, which is in line with Monras (Forthcoming) and with the more conservative estimates among the ones shown in Table 1. In this case, with an inverse local labor demand elasticity of .7 we have that internal migration accounts for around 66 percent of the wage recovery, and that the internal migration elasticity is about 2.3. This estimate, thus, also squares well with the estimates of the Mariel Boatlift episode and with other literature.

Table 4 goes around here

In the fourth row, I assume that the local labor demand is more inelastic, with a value of 1.4. In this case, we obtain estimates that suggest that internal migration only accounts for 33 percent of the wage recovery, and hence, this implies a larger role for technology adoption. Row 5 shows that had we had a higher number for the migration response then obviously the role of internal migration would have been larger.

5 Conclusion

In this paper I use the Mariel Boatlift to estimate, through the lenses of a small open economy model of a metropolitan area, the relative importance of internal migration and local technology adoption in dissipating wage effects resulting from immigrant-driven labor supply shocks. To do so, I start by documenting short-run declines in wages of low-skilled workers in Miami relative to workers in other cities and relative to higher skilled workers. This variation allows to estimate the short-run local labor demand elasticity. Next, I show that internal migration seems to respond to this local shock during the second part of the decade of the 1980s. This seems to coincide with a recovery of wages in Miami.

I then develop a model that helps to analyze the relative contribution of technology adoption and internal migration to this recovery of wages in Miami. Intuitively, the model rationalizes the recovery that cannot be explained by internal migration as changes in local technology or capital that are biased towards particular factors of production, in the case of Miami, low-skilled workers. In line with the model, I document that in the longer-run, i.e. between 1980 and 1990, wages in Miami of all education groups were not lower than in other local labor markets despite the large inflow of workers following the Mariel Boatlift. At the same time, we see an increase in the supply of low skilled workers in Miami that is smaller than what would have been predicted by the size of the Mariel Boatlift shock. This suggests that internal migration might have helped in the wage recovery, but that other factors were also potentially important.

Through the lenses of the model and given the estimates that I report in this paper, the evidence suggests that around 50 percent of the wage recovery is explained by the technology adopted at the local level, while the rest can be explained by the role of internal migration as emphasized in classical spatial equilibrium models.

6 Figures

Figure 1: Graphical representation of the model

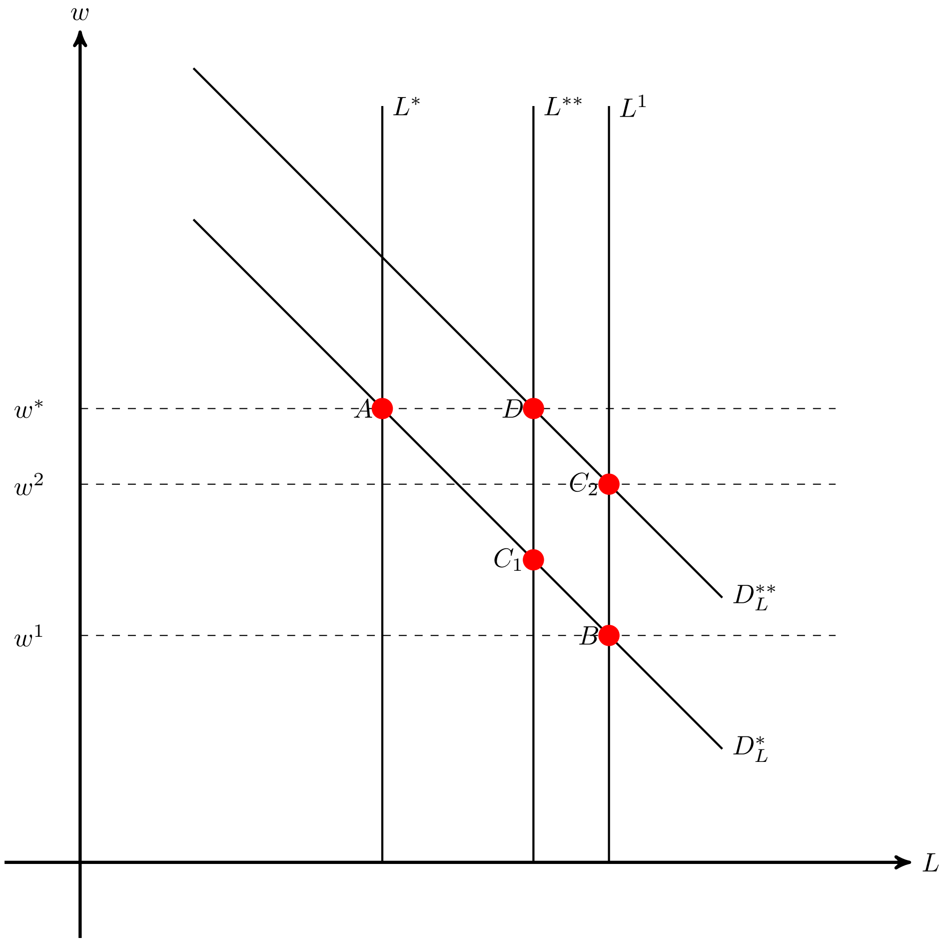
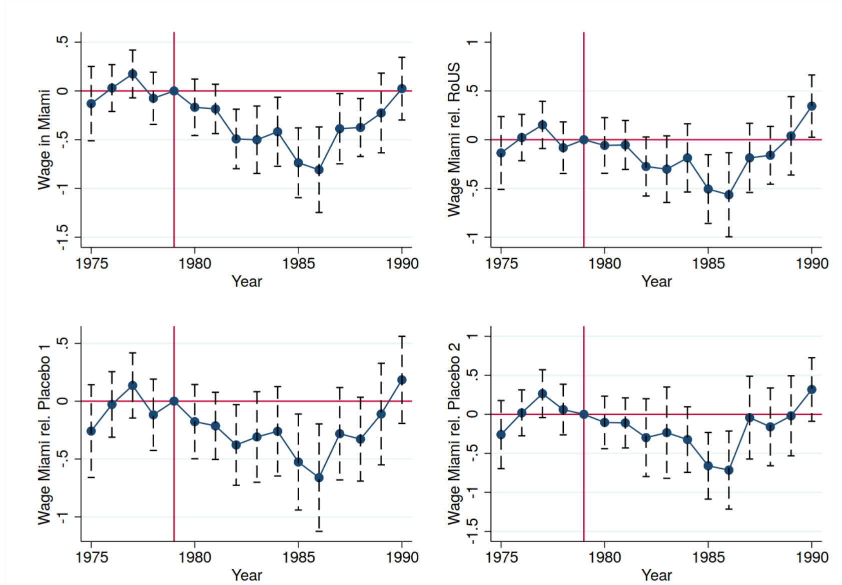
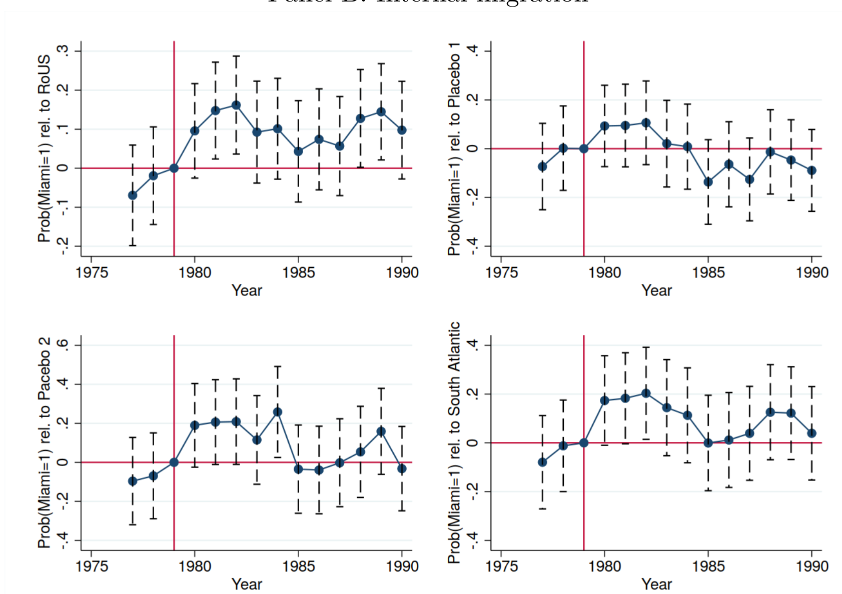


Figure 2: Wage dynamics and internal migration

Panel A: Wages



Panel B: Internal migration



Notes: The graphs in Panel A of this figure show the wage dynamics of low-skilled workers in Miami relative to 1980 (top-left graph), relative to the Rest of the US (RoUS, top-right graph), relative to the Card control group (bottom-left graph) and relative to the Borjas control group (bottom-right graph), see Borjas (2017) for more details on the definitions of the different comparison groups. The graphs in Panel B of this figure show the relative share of low-skilled workers in Miami relative to the rest of the US (top-left graph), relative to the Card control (top-right graph), relative to the Borjas control (bottom-left graph) and relative to the rest of cities in the South Atlantic region (bottom-right graph). Vertical lines display 95 per cent confident intervals.

7 Tables

Table 1: Estimation of the causal effect of Cuban immigration on wages and internal migration

Panel A: **Wages of Low-Skilled Workers, March supplement**

VARIABLES	(1) (ln) wage OLS	(2) (ln) wage OLS	(3) (ln) wage OLS	(4) (ln) wage OLS	(5) (ln) wage OLS	(6) (ln) wage OLS
Post x Miami	-0.239	-0.273	-0.330	-0.0992	-0.119	-0.197
	(0.0828)	(0.0891)	(0.110)	(0.0805)	(0.0902)	(0.109)
Observations	14,105	1,755	855	14,105	1,755	855
Year FE	yes	yes	yes	yes	yes	yes
Metarea FE	yes	yes	yes	yes	yes	yes
Controls	no	no	no	yes	yes	yes
Comparison to	all metropolitan areas	Card's control group	Borjas' control group	all metropolitan areas	Card's control group	Borjas' control group

Panel B: **Wages of Low-Skilled Workers, ORG files**

VARIABLES	(1) (ln) wage OLS	(2) (ln) wage OLS	(3) (ln) wage OLS	(4) (ln) wage OLS	(5) (ln) wage OLS	(6) (ln) wage OLS
Post x Miami	-0.0915	-0.0724	-0.145	-0.0670	-0.0271	-0.0969
	(0.0444)	(0.0484)	(0.0510)	(0.0422)	(0.0468)	(0.0491)
Observations	19,240	2,388	1,213	19,240	2,388	1,213
Year FE	yes	yes	yes	yes	yes	yes
Metarea FE	yes	yes	yes	yes	yes	yes
Controls	no	no	no	yes	yes	yes
Comparison to	all metropolitan areas	Card's control group	Borjas' control group	all metropolitan areas	Card's control group	Borjas' control group

Panel C: **Short-run inverse local labor demand elasticity**

VARIABLES	(1) Inflows of Cubans First-stage	(2) Inflows of Cubans First-stage	(3) Δ (ln) wage OLS	(4) Δ (ln) wage OLS	(5) Δ (ln) wage IV	(6) Δ (ln) wage IV
Share of Cubans in 1980	1.260	1.262				
	(0.0529)	(0.0532)				
Inflows of Cubans			-1.313	-1.350	-1.264	-1.310
			(0.338)	(0.346)	(0.320)	(0.322)
Change in native population		-0.00163		0.0388		0.0385
		(0.00117)		(0.0450)		(0.0382)
Observations	152	152	152	152	152	152
Education FE	yes	yes	yes	yes	yes	yes
Metropolitan area FE	yes	yes	yes	yes	yes	yes
Metropolitan areas	all	all	all	all	all	all

Notes: Panel A and B of this table shows the estimates of the relative wages in Miami relative to various control groups of cities in 1981 to 1985 relative to before 1981. Panel A uses March CPS data, Panel B uses ORG CPS data. All the metropolitan areas refers to the 38 or 45 cities covered by the March CPS and CPS ORG throughout the period. Card's control group includes Atlanta, Houston, Los Angeles, and Tampa and Borjas'control group includes Anaheim, Rochester, Nassau-Suffolk, and San Jose. See details in the text and in Borjas (2017). Panel C replicates and expands the results reported in Borjas and Monras (2017). Controls include age, race and occupation (only in Panel A) dummies. Robust standard errors are reported in parenthesis.

Table 2: Estimation of the causal effect of Cuban immigration on wages and internal migration

Panel A: **Internal Migration of Low-Skilled Workers**

VARIABLES	(1) Prob(Miami=1) probit	(2) Prob(Miami=1) probit	(3) Prob(Miami=1) probit	(4) Prob(Miami=1) probit
years 1981-1984	0.124	0.0675	0.203	0.139
	(0.0321)	(0.0446)	(0.0582)	(0.0494)
years 1985-1990	0.0945	-0.0341	0.0563	0.0370
	(0.0292)	(0.0403)	(0.0541)	(0.0453)
Observations	44,845	10,668	3,971	6,643
Controls	yes	yes	yes	yes
Comparison to	all metropolitan areas	Card's control group	Borjas' control group	South Atlantic region

Panel B: **Internal Migration of High-Skilled Workers**

VARIABLES	(1) Prob(Miami=1) probit	(2) Prob(Miami=1) probit	(3) Prob(Miami=1) probit	(4) Prob(Miami=1) probit
years 1981-1984	0.0249	0.00964	0.0640	0.0392
	(0.0205)	(0.0281)	(0.0311)	(0.0296)
years 1985-1990	0.0485	-0.0128	0.0848	-0.0475
	(0.0180)	(0.0247)	(0.0275)	(0.0260)
Observations	181,054	29,357	17,345	25,783
Controls	yes	yes	yes	yes
Comparison to	all metropolitan areas	Card's control group	Borjas' control group	South Atlantic region

Notes: Panel A of this table shows the estimates of the relative wages in Miami relative to various control groups of cities in the 1980s relative to the 1970s. All the metropolitan areas refers to the 38 cities covered by the March CPS throughout the period. Card's control group includes Atlanta, Houston, Los Angeles, and Tampa and Borjas'control group includes Anaheim, Rochester, Nassau-Suffolk, and San Jose. See details in the text and in Borjas (2017). Panels B and C of this table estimate the probability of being in Miami for low- (Panel B) and high-skilled workers (Panel C) in different periods of time over the 1980s relative to the years before the Mariel Boatlift shock using a probit model. Controls include age and race dummies. Robust standard errors are reported in parenthesis.

Table 3: Estimation of the causal effect of Cuban immigration on long-run wages and internal migration

VARIABLES	(1) Inflow of Cubans First-stage	(2) Inflow of Cubans First-stage	(3) Δ (ln) wage OLS	(4) Δ (ln) wage OLS	(5) Δ (ln) wage IV	(6) Δ (ln) wage IV	(7) Δ share low-skilled OLS	(8) Δ share low-skilled IV
L.Share of Cubans, Census	0.716	1.231						
	(0.0169)	(0.0845)						
Inflow of Cubans			-0.188	-0.228	0.113	-0.0858	0.604	0.641
			(0.200)	(0.201)	(0.517)	(0.198)	(0.0903)	(0.113)
Observations	38	152	38	152	38	152	38	38
Sample	HSDO	all	HSDO	all	HSDO	all	all	all
Education FE	no	yes	no	yes	no	yes	no	no
Metropolitan area FE	no	yes	no	yes	no	yes	no	no
widstat					1797	212.3		1797

Notes: This table estimates the effect of the inflow of Cubans in 1980 (as a fraction of the low-skilled labor force) on the low-skilled wage change and the change in the share of low-skilled workers between 1980 and 1990. Columns (2) and (4) use the share of Cubans in the labor force in each location in 1980 as an IV strategy. This table uses variation from the 38 metropolitan areas available in the CPS data throughout this period. 'widstat' indicates the F-stat of the excluded instrument in the first stage regression.

Table 4: Contribution of internal migration and local technology adoption to wage recovery

	Inv. labor demand elasticity $1/\hat{\sigma}$	Internal migration response $\hat{\lambda}$	Technological Adoption $\hat{\nu}$	Contribution to wage recovery Technology:	 Internal migration:	Internal migration elasticity
Baseline	1.0	0.4	0.5	48%	52%	1.6
Very Elastic LD	0.4	0.4	0.2	19%	81%	4
Elastic LD	0.7	0.4	0.3	34%	66%	2.3
Inelastic LD	1.4	0.4	0.7	67%	33%	1.1
higher-Internal	1.0	0.6	0.3	32%	68%	2.4

Notes: This table provides estimates on the relative contribution of technological adoption and internal migration in dissipating the wage effects of immigrant-driven labor supply shocks on the local labor market. The baseline estimates of the inverse labor demand elasticity follow Borjas and Monras (2017). Table 3 provides estimates of the internal migration response. Technological adoption is estimated using the model as explained in section 3.6. 'LD' refers to labor demand.

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