How Do Very Open Economies Absorb Large Immigration Flows?

Recent Evidence from Spanish Regions

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Abstract. In recent years, Spain has received an unprecedented immigration flow. Between 1999 and 2006, the fraction of the working-age population that was foreign-born increased from 2 to 12 percent. We study how Spanish regional economies have adjusted to this large inflow, along several potential channels. We identify the exogenous supply shock to regional labor supplies using historical immigrant settlement patterns by country of origin. Using data from the Labor Force Survey and the decennial census, we find that immigration has not significantly reduced the regional employment rates of workers in the same education category. Instead, the adjustment took place through the typical industry in the region employing types of labor with higher immigrant penetration more intensively. Second, we do not find an expansion in the scale of the typical industry in immigrant-receiving regions. Overall, and perhaps surprisingly, this pattern is very similar to how US local economies absorbed immigration flows in recent decades.

JEL Codes: J2, F1, O3.
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1. Introduction

This paper studies how open economies adjust to shocks to the size and skill composition of their labor forces. Using data on the very large immigration wave recently experienced by Spain, we provide causal estimates of several channels by which Spanish regional economies have absorbed the inflows.

Empirical research on the effects of immigration on local or regional economies has flourished in the last few years (Card 2001, Hanson and Slaughter 2002, Lewis 2003, among others). This line of work has been motivated by the mounting evidence against the usefulness of the standard one-good, closed-economy model as a framework to analyze the economic effects of immigration.

Regional economies are textbook examples of (very) open economies: there are no formal barriers to trade among regions within a country, and technology and institutional differences among regions are usually small. As a result, there are several potential channels by which economies can absorb immigration shocks, in addition to changes in the wage structure (which was the focus in the early literature following the closed-economy model). In particular, flows of workers and capital across regional borders may play an important role. Card and DiNardo (2000) argue that this channel has been relatively unimportant for US metropolitan areas. However, the question is still open and little evidence exists for countries other than the US.

Spain's recent immigration experience is potentially very informative, because of its unusually high impact on the size and skill composition of regional labor forces and the large cross-sectional variation. Between 1999 and 2006, the foreign-born share in the working-age population increased from 2 to more than 12 percent. Across Spanish regions, the foreign-born share ranged from below 4 to above 26 percent in 2006.[1] Additionally, the educational attainment of the average immigrant was well below that of the average native, for individuals in the age group 25-45.

Moreover, our analysis provides estimates on how regional economies in continental Europe are affected by immigration shocks. A priori, the higher degree of wage rigidity and regulation in European labor markets relative to the US suggests the possibility that the channels by which immigration shocks are absorbed differ from the US experience. Methodologically, our analysis is very similar to that of Lewis (2003) for US metropolitan areas, which allows for a straightforward comparison between the estimates for the two countries.[2]

More specifically, the channels of adjustment we explore and the results we find are the following. First, did natives react to immigration by migrating to other regions, thus offsetting the impact on the skill distribution in high immigration regions? Our analysis suggests the answer is no. In fact, native migration seems to have reinforced the location choices of foreign-born migrants. Secondly, did regional employment rates fall for the skill groups that experienced large immigration-driven increases in size? We find that employment rates remained essentially unaffected. Thirdly, did regional economies accommodate the inflows by changing their output mix, as would be predicted by a Heckscher-Ohlin open-economy model? Again, our results suggest that this was not the case. Finally, did industries in high immigration regions absorb immigration by adapting their factor intensities to the change in the skill distribution? Our estimates strongly suggest the latter channel as the most important absorption mechanism.

[1] Based on local registry data.
[2] See also Dustman and Glitz (2007) for Germany.

Perhaps surprisingly, our results are, overall, very similar to those in Lewis (2003). This suggests that Spanish regional economies between 2001 and 2006 have adjusted to immigration much in the same manner as US metropolitan areas over the 1980s.

2. Data and Methodology

2.1 The Setup

Administratively, Spain is divided in 52 provinces. This division is based to a large extent on historical and cultural boundaries and does not bisect metropolitan areas. In what follows, we will use the terms "province" and "region" interchangeably. Let r = 1,…,52 index Spanish regions. We define regional labor markets by education level. We consider three education levels: high school dropouts, high school graduates, and college graduates, denoted by e = 1, 2, 3. We consider two time periods, t = 2001, 2006, and J industries, j = 1, …, J.

Let the number of potential workers in region-education cell (r,e) in year t be denoted by L_{ert}, and its change over the five year period 2001-2006 by $\Delta L_{er} = L_{er,2006} - L_{er,2001}$. In our application we focus on the age group 25-45.[3] The population in a given (r,e,t) cell is either employed (N) or non-employed (U), so that $L_{ert} \equiv N_{ert} + U_{ert}$.

Let us define employment-population ratios as $NR_{ert} = N_{ert} / L_{ert}$, for region-education cell (r,e) in year t. As before, let the change be given by $\Delta NR_{er} = NR_{er,2006} - NR_{er,2001}$. Employment is distributed across the different industries, so that $N_{ert} = \sum_j N_{erjt}$. Finally, let

[3] This is the age group in the working-age population whose size and skill composition was most affected by recent immigration.

M_{ecr} denote the inflow of foreign-born workers with education level e from country of origin c to region r during the period 2001-2006, so that $M_{er} = \sum_c M_{ecr}$.

We thus need data on total population, migration inflows, employment and industry composition at the regional level and by education, in 2001 and 2006. Our main source of data is the Spanish Labor Force Survey (EPA) for 2001 and 2006 (second quarter). The EPA contains detailed individual-level information on region, education level, age, employment status, country of birth and industry. When constructing the immigrant flows, we supplement the Labor Force Survey with data from the decennial census, in order to take advantage of its larger number of observations.[4]

The Labor Force Survey data suggest that recent immigrant inflows have been disproportionately less educated than natives in most regions. In the 25 to 45 age group, about 26 percent of the foreign-born population in 2006 did not have a high school degree, compared with only 13 percent of the native population. Figure 1 shows the fraction of high school dropouts among both immigrants and natives across the 52 regions, together with the 45-degree line. In most regions, the fraction of unskilled workers was considerably higher among the foreign-born population.

2.2 Channels of Adjustment

Given this setup, we explore the channels through which regional economies in Spain have adjusted to the large recent immigration inflow. A first potential channel of adjustment involves native interregional mobility.

[4] We estimate the immigrant flow between 2001 and 2006, M_{er}, as the difference between two stocks: foreign-born individuals aged 25-45 in the 2006 EPA and foreign-born individuals aged 20-40 in the 2001 Census. We could use the 2001 EPA instead of the 2001 Census, but the Census is clearly better in terms of number of observations. Note that for many regions the density of immigrants in 2001 was still very low.

2.2.1 Displacement of natives

In the context of US immigration, several authors, starting with Borjas et al. (1996), have highlighted the possibility that a migration inflow that alters the local skill composition may well trigger native out-migration that cancels out potential labor market effects. In the extreme case, if each immigrant of education level e in region r drives out a native in the same education cell, the migration inflow would leave population size and skill composition in the region completely unchanged, thus no labor market adjustments would take place at the regional level.

Our first step, then, is to analyze the extent to which the immigrant flow between 2001 and 2006 altered regional labor supplies.[5] We thus estimate the following regression model:

Displacement Effect

$$(1) \qquad \frac{\Delta L_{er}}{L_{er,2001}} = \%\Delta L_{er} = \beta \frac{M_{er}}{L_{er,2001}} + \alpha_e + \mu_r + \varepsilon_{er}$$

The dependent variable is the percent change in the population of education level e in region r, and the explanatory variable of interest is the immigrant inflow in each (r,e) cell as a proportion of population size in the cell in 2001. The specification includes region as well as education fixed effects.

Note that a β equal to zero would imply that an inflow of immigrants would have absolutely no effect on the size of the cell, due to full displacement of native workers. On the other hand, a β equal to 1 would imply no displacement, that is, a 1% immigrant inflow would have led to a 1% increase in the population.

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[5] A similar analysis of displacement effects of immigration across US metropolitan areas can be found in Card and DiNardo (2000).

Table 1 presents some descriptive statistics for the variables of interest. On average, the migration inflow between 2001 and 2006 amounted to about 10 percent of the initial population by region and education level, with a large variance across cells. During the same period, total population aged 25 to 45 increased by about 6 percent in the average cell. By education, the size of the immigrant inflow was on average about 13 percent of the 2001 high school dropout population, compared with 9 percent of the initial population of both high school and college graduates.

2.2.2 Employment rates

If the immigrant inflow did lead to changes in the size and composition of the regional labor force, a simple closed-economy model would predict that the supply shock should lead to changes in relative wages and employment rates.[6] In particular, an increase in the relative supply of workers in education level e should have led to a decline in both the employment and the wage rate in the cell.[7] In order to test this prediction, we estimate the following regression model:

Employment Effect

$$(2) \qquad \frac{\Delta NR_{er}}{NR_{er,2001}} = \%\Delta NR_{er} = \gamma\%\Delta L_{er} + \alpha_e + \mu_r + \varepsilon_{er}$$

The dependent variable is the percent change in the employment to population ratio, and the main explanatory variable is the percent change in the size of each (r,e) cell. We expect

[6] In the basic closed-economy model typically used in spatial correlation studies, one final good is produced by means of a constant-returns-to-scale, constant-elasticity-of-substitution production function. The factors of production are different types of labor, defined by education level. In addition, employment-population ratios for a given education type are assumed to be an increasing function of the wage paid to that type of labor. See Altonji and Card (1991) and Card (2001) for two variations on the basic model.

[7] In the basic model, wages and employment rates in equilibrium are solely a function of the vector of potential workers in the economy. An increase in the number of potential workers of a given type leads to a reduction in the wages and employment rates of that type (although the total employment of workers of that type increases).

that γ will be negatively signed, measuring the elasticity of the employment rate of an education group in response to a 1% increase in the population with the same level of education.

A large literature has estimated similar models with US data, reaching the conclusion that immigration has had at most a moderate impact on overall employment rates (for some recent examples, see Card 2005 and Lewis 2003).

Table 1 shows that total employment ($\%\Delta N_{er}$) increased by 15 percent in the average region-education cell between 2001 and 2006. This translated into an increase in the employment to population ratio ($\%\Delta NR_{er}$) of 7.4 percent (from 69.7% in 2001 to 74.5% in 2006), although the degree of variation across cells was large.

A natural extension would be to estimate equation (2) using the change in the wage rate as a dependent variable. Data limitations prevent us from undertaking this analysis for the Spanish case.[8] However, note that in the standard model in this literature, such as the one in Card (2001), changes in employment rates take place if and only if there are changes in wage rates.[9]

2.2.3 Output mix

Surprisingly small employment and wage effects have been found consistently in the US literature, which has prompted researchers to move towards an open economy framework in order to examine additional potential channels of adjustment to immigration.[10] The well-known Rybczinsky theorem (Rybczinski, 1955) states that following an inflow of potential

[8] The Spanish Labor Force Survey (and Census) lacks information on wages or income.

[9] In the context of the basic model outlined above, aggregate employment rates are increasing in wages. As a result, as the wage of the factor that has experienced an increase in supply falls, its employment rate will also fall. This will mitigate the effect of immigration on wages by reducing the aggregate labor supply. Thus, an inflow of potential workers of one type will reduce the relative wage and the employment rate for that type of labor. In other words, in the context of the model, finding an effect of immigration on employment rates offers indirect evidence for effects on relative wages.

[10] See Hanson and Slaughter (2001), Lewis (2003).

workers into an open economy, it is theoretically possible that the wage structure (and thus aggregate employment rates) remains unaffected, but changes in the sectoral composition of employment and output take place. In the absence of prohibitive barriers to trade across regions, changes in the skill composition of the local labor force would lead to changes in the composition of output. Regions receiving immigration flows that alter their skill distribution would expand production in sectors that use the relatively more abundant factors more intensively (while reducing the scale of production in the other sectors). Under the premises of the theorem, in the new equilibrium employment and wage rates would remain unchanged.[11]

Thus, next we test the extent to which regional economies have adjusted to immigration flows by changing their industry mix, while keeping their initial factor requirements unchanged. This is what we call the "between-industry" adjustment. In order to estimate this "between-industry" effect, we decompose the change in population in a given (r,e) cell as follows.

For each education level, the change in the size of the potential labor force, $\%\Delta L_{er}$, must be absorbed by either and increase in non-employment, or by an increase in employment in the industries in the region:

$$(3) \qquad \frac{\Delta L_{er}}{L_{er,2001}} = \%\Delta L_{er} \equiv \frac{\Delta N_{er}}{L_{er,2001}} + \frac{\Delta U_{er}}{L_{er,2001}}$$

The increase in employment, in turn, can take place through either an increase in industry scale at the initial factor intensities (the "between industry" effect, BE), or through changes in factor intensities at the initial industry scale (what we can call the "within-industry"

[11] See Leamer (1995) for a more detailed description.

effect, WE), or by an interaction of both (IE). Formally, the increase in employment can be decomposed as follows:

$$\frac{\Delta N_{er}}{L_{er,2001}} \equiv \sum_j \frac{N_{erj,2001}}{L_{er,2001}} \cdot \%\Delta N_{rj} + \sum_j \frac{N_{erj,2001}}{L_{er,2001}} \cdot \%\Delta\left(\frac{N_{erj}}{N_{rj}}\right) + \sum_j \frac{N_{erj,2001}}{L_{er,2001}} \cdot \%\Delta N_{rj} \cdot \%\Delta\left(\frac{N_{erj}}{N_{rj}}\right)$$

(4)

$$= BE_{er} + WE_{er} + IE_{er}$$

Where the ratio $\frac{N_{erj,2001}}{L_{er,2001}}$ measures the employment level in industry j in 2001 as a share of total population in the (r,e) cell (i.e. the initial "weight" of industry j in each cell), N_{rjt} is the overall scale of industry j (measured in number of workers), and where $\frac{N_{erjt}}{N_{rjt}}$ indicates the intensity with which industry j uses workers of education level e, in region r.[12]

On average, the industries with the largest initial scale measured by employment ($N_{rj,2001}$) were manufacturing, retail and construction. However, between 2001 and 2006, industry scale increased the most for the domestic services sector, which more than doubled in size, followed by production utilities and real estate services. At the other end, the scale of the fishing sector significantly fell.

Regarding factor intensities (N_{erj}/N_{rj}), the sectors that used high school dropouts most intensively in 2001 were domestic services, agriculture and fishing, while college graduates were employed most intensively in the education, health and finance sectors. Between 2001 and 2006, all sectors reduced their intensity in the use of high school dropouts, while increasing their use of high school and college graduates.

[12] This decomposition was introduced by Lewis (2003), who adapted it from the labor literature on income inequality, and has recently been used in Card (2005).

In words, the "between effect" is the increase in the total employment of e-type workers in region r that arises purely from the increase in the size of the industries in the region, assuming that the industry composition of employment by education in the region remains fixed at its 2001 values.[13] Table 1 shows that (weigthed) industry scale (BE_{er}) increased by almost 14% on average between 2001 and 2006.

The "within effect", in turn, is a weighted sum of the growth in the relative intensity of e-type labor in the industries in the region between 2001 and 2006.[14] Finally, there is an interaction term, IE_{er}, that collects the increase in the use of e-type labor in the region due to simultaneous changes in scale of a sector and the relative intensity with which it is used.

Our test of the importance of the "between-industries" effect proceeds by estimating the following regression model.

Output Mix Effect

$$(5) \qquad BE_{er} = \lambda\%\Delta L_{er} + \alpha_e + \mu_r + \varepsilon_{er}$$

Note that coefficient λ will inform us of the proportion of the total change in the population that has been absorbed through changes in output mix in a region, at the initial factor intensities.[15] In its strict form, the Rybczinsky effect requires that all of the increase in employment (BE + WE + IE) is absorbed through the "between effect" for traded goods. That is, a given increase in employment for a type of labor in a region should be fully

[13] For example, suppose that the scale of agriculture has increased by 10% in region j and all other sectors have not changed their size, measured by employment. Furthermore, suppose that agriculture is 10% of the total employment of type e in the region. Then the percentage increase in the economy's demand for e-type labor (the BE term) will be 1%.

[14] Suppose now that agriculture has reduced in 50% its use of e-type labor. Being only 10% of the economy in 2001 (in terms of employment of type e), the total demand for this type of labor due to the within effect would have fallen by 5%.

[15] We use a one-digit industry definition. The 17 industries are: agriculture and farming, fishing, mining, manufacturing, production utilities, construction, retail, restaurants and hotels, transport, finance, real estate, legal and business services, public administration, education, health, other social services and domestic services.

absorbed by a growth in the scale of the industries that tend to employ that type of labor. In the other extreme case, an estimate of λ equal to zero would reject the existence of a Rybczinsky effect.

Note also that we can estimate parallel regression models where the dependent variable is each of the remaining components of $\%\Delta L_{er}$ (the within effect, WE_{er}, the interaction effect, IE_{er}, and the non-employment effect, UE_{er}), and that the four resulting λ coefficients would sum up to one by construction.

2.3 Estimation Issues

Our three regression models (equations 1, 2 and 5) attempt to estimate the causal effect of migration inflows on the composition of the regional labor force, and in turn the effect of those changes in the composition of the labor force on employment rates and industry mix.

A crucial concern is the potential endogeneity of (both internal and international) migration flows. Unobserved economic fluctuations at the (r,e) level can drive employment rates and industry mix, as well as the location decisions of both natives and immigrants. Note that we account for the possibility of non-synchronized regional business cycle effects through the inclusion of region fixed effects. We also incorporate potential skill-biased technological change at the national level by including education fixed effects.

However, it is still possible that there are unobserved region-education specific demand shocks that drive employment as well as location and migration decisions. In order to deal with the potential remaining endogeneity, we instrument the change in worker composition using the exogenous variation given by historical immigrant settlement patterns. This strategy is common in the immigration literature[16] and relies on the fact that recent immigrants tend to locate in geographical areas where previous cohorts of immigrants from the same country of origin have settled in the past, due to network effects. If this is the case, we would have a supply-driven shock to the local labor force, which we can use to instrument M_{er} and $\%\Delta L_{er}$.

More specifically, we construct our instrument, Z_{er}, by using the geographical distribution of immigrants by country of origin across Spanish regions in 1991 (constructed using 1991 Census data).[17] The precise definition is the following:

(6) $$Z_{er} = \sum_c Z_{erc} = \sum_c \pi_{rc,1991} \cdot M_{ec}$$

Where M_{ec} is the inflow of immigrants from country of origin c and education level e in the 2001-2006 period *to the whole of Spain*, and $\pi_{rc,1991}$ is the proportion of immigrants from country c that were located in region r in 1991. Thus, the overall recent inflow of immigrants from each country of origin (M_{ec}) is artificially "assigned" to each region according to the 1991 geographical distribution of immigrants by country of origin.[18] The instrument then aggregates all countries of origin to provide an "imputed" immigrant inflow for each (r,e) cell. Table 1 shows that the average imputed inflows coincide with the actual ones (by construction), although the ranges of variation differ considerably.

Our instrument Z_{er} is thus exogenous to economic conditions during the 2001-2006 period, provided that post-2001 economic fluctuations at the (r,e) level are uncorrelated

[16] Some of the previous papers using a similar instrument are Card (2001), Saiz (2003), Ottaviano and Peri (2006), Lewis (2003) and Saiz (2007).
[17] Note the 5% sample of the 2001 Census only provides 17 country of origin categories.
[18] Most of the immigrants during the 2001-2006 period have originated from South America, Eastern Europe and Morocco. In 2006, the most common countries of origin among the foreign-born population in Spain were Morocco (13.6%), Ecuador (10.3%), Romania (8.9%), Colombia (6.4%), the UK (6.4%) and Argentina (6.1%), according to local registry data.

with pre-1991 immigrant location decisions by country of origin. The remaining question, then, is whether settlement patterns by country of origin pre-1991 are in fact correlated with the location decisions of recent immigrants.

This type of instrument has been shown to be valid for the US, where immigration flows have been very large since 1965 and many decades of high-quality data are available. It is a priori unclear whether it will work for the case of Spain. The large boom in immigration started around year 2000, and the population of foreign-born individuals in Spain in the early 1990's was small. We explore the predicting power of our instrument by estimating the following set of regressions:

(7) $$M_{erc} = \delta Z_{erc} + \alpha_{ec} + \mu_{rc} + \varepsilon_{erc}$$

For each country of origin, we estimate the relationship between our "imputed" inflows (Z_{er}) and the actual immigration flows (M_{er}). Then we aggregate all countries of origin and estimate the following combined specification.

(8) $$M_{er} = \delta Z_{er} + \alpha_e + \mu_r + u_{er}$$

The results can be found in table 2. "Imputed" migration flows are significantly associated with actual inflows for all countries of origin (except "other Africa"). The coefficients range from 0.3 to 2.3, and the R^2 from 14 to 89%, depending on the country. The combined specification indicates that the instrument (together with the two sets of fixed effects) predicts 80% of the actual migration inflow (as indicated by the R^2, not shown in the table). The coefficient is 0.75 and strongly significant.

These results show that Z_{er} is a strong instrument for M_{er} (actual migration flows), the explanatory variable in equation 1. In the specifications for employment and industry mix (equations 2 and 5), the variable to be instrumented is $\%\Delta L_{er}$. Thus before reporting the second-stage results of those specifications in section 3, table 3 shows the results of the first-stage regression, which is the following.

$$(9) \qquad \%\Delta L_{er} = \eta \frac{Z_{er}}{L_{er,2001}} + \alpha_e + \mu_r + u_{er}$$

Note the instrument has been expressed as a proportion of the 2001 population in each cell, so that both dependent and independent variable have the same normalization. Table 3 reports the results from several different specifications. The first one includes all 156 (r,e) cells and is unweighted. The second column weighs each cell by the square root of its 2001 population ($L_{er,2001}$). Columns 3 to 6 drop the cells with very small size in 2001. Finally, column 6 has robust standard errors that are clustered at the supra-regional level, since Spanish provinces are grouped into 17 larger "states" with common parliament and legislation. The table shows the first stage is very strong, i.e. our "imputed" migration inflows do a good job at predicting recent changes in the size of the potential labor force at the region-education level. This finding implies that foreign-born immigration significantly altered the skill composition of the labor force in Spanish regions.

3. Results

3.1 Displacement

Table 4 reports the results of estimating the regression model shown in equation 1. The dependent variable is the percent change in the potential labor force in a given (r,e) cell ($\%\Delta L_{er}$), and the main explanatory variable is the migration flow into that cell between 2001 and 2006 (M_{er}).

The table reports both OLS and IV specifications. The OLS specifications show estimated coefficients that are always significantly different from zero and larger than 1 in magnitude. This suggests that the immigrant flows have not displaced native workers in the same region and education level.

Since one may worry that the location decisions of both native and immigrants are driven by unobserved economic conditions that may vary at the region-education level, we instrument the actual migration flows with the "imputed" flows described in section 2.3, thus using the exogenous variation generated by early migrant settlements and their "pull" effect over recent immigrants. The IV results confirm that migrant inflows do not appear to have displaced native workers.[19]

3.2 Employment Rates

Having confirmed that the recent immigrant inflows significantly affected the size and composition of the labor force across Spanish regions, standard closed economy models would predict changes in relative wages and relative employment rates. Table 5 reports the results of estimating equation 2, where the dependent variable is the percent change in the regional employment rate of workers of a given education level ($\%\Delta NR_{er}$) and the explanatory variable of interest is the change in the size of the potential labor force ($\%\Delta L_{er}$).

The OLS results show that region-education cells that received a higher inflow of immigrants did not experience a significant decline in the overall employment rate. In fact, coefficients are positive in all specifications and significant in most of them. A 1% increase

[19] Card and DiNardo (2000) also find no displacement effect of immigration across US metropolitan areas. Our finding for Spain confirms our prior, based on the lower geographical mobility of native-born workers within Spain relative to the estimates for the US.

in the labor force in a given cell is associated with a 0.7 to 1% increase in the employment rate.

Again, endogeneity concerns lead us to focus on the IV specifications (first stages shown in table 3). The first two columns suggest that once we account for the endogeneity of migration inflows, their effect on employment is in fact negative, as expected, although the estimated elasticities are small and not significantly different from zero. Moreover, once we drop the cells with very small sizes in 2001, the estimated effects are positive and remain mostly insignificant.

Overall, the results suggest that the large immigration inflow that took place in Spain between 2001 and 2006 did not harm the employment rates of natives.[20]

3.3 Industry Structure

According to the standard Hecksher-Ohlin model, an increase in the supply of one type of potential workers will either i) lead to a reduction in the relative wage (and thus the relative employment rate) of that type, or ii) will not affect the wage structure but will lead to an expansion of the sectors that use that factor relatively more intensively, while not affecting the factor intensities in any industry. In this case, trade across regions would lead to factor price equalization (the "Rybczinsky effect"), so that the migration inflow would not affect local employment or wages.

Regions would simply adjust to the labor supply shock by specializing more in the sectors that use the now relatively more abundant factor more intensively. For instance,

[20] Using a different approach, a recent paper by Carrasco et al. (2007) finds no significant effect of immigration on employment rates at the national level in Spain for the second half of the 1990's.

regions that receive a larger inflow of high school dropouts would expand their production of the goods and services that require a more intensive use of high school dropouts.

We have shown so far that migrant inflows affected regional labor forces, but left regional employment rates by education level unchanged.[21] This speaks against prediction i). Thus our next step is to test for prediction ii), the Rybczinksy-type adjustment.

3.3.1 Output mix

The "between-industry" regressions, shown in table 6, show the proportion of the inflow that has been absorbed through changes in industry mix, keeping initial factor intensities constant (equation 5).

The first panel includes all 17 industries in the analysis. The OLS results suggest that between 7 and 9 percent of the population increase of a given education level was absorbed through changes in the output mix. In the IV specifications, the estimated size of the effect increases slightly to 10 to 13 percent, but significance levels are low.

According to the Rybczinsky theorem, immigration would be absorbed through changes in trade and sectoral specialization across regions. This suggests that the changes in output mix driven by immigration should take place mostly in traded sectors (Ethier, 1972). Thus the second panel of table 6 shows the results of estimating the between-industry effects only for traded sectors.[22]

Once we restrict the analysis to traded sectors, the OLS effects become very close to zero and statistically not significant. The IV results suggest that changes in the output mix account for 3 to 4% of the increase in potential labor supply, but these effects are not significantly different from zero.

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[21] Recall that under the model in Card (2001), this implies that wages have not been much affected either.

[22] We follow the classification of traded sectors suggested by Hanson and Slaughter (2002) and followed by Lewis (2003).

Our between-industry regression results suggest that, at least at the level of industry dissagregation analyzed, regional economies did not adjust to the immigrant inflow by increasing specialization in the industries that used the more abundant type of worker more intensively. This rejects the Rybczinsky-type effect predicted by open economy models. This result is in line with the findings in Lewis (2003) for US metropolitan areas.[23]

Thus so far we have found that the large labor supply shocks induced by immigration did not result in lower overall employment rates, or in increasing specialization across regions through changes in industry mix. Therefore, it follows that the existing industry structure must have accommodated the increasing supply of labor by using more intensively the type of worker that became relatively more abundant (typically, high school dropouts). This is what we test in the next section.

3.3.2 Worker mix

What fraction of the worker inflow has been absorbed by changes in worker mix, keeping the initial industry scale constant? This is what we called the "within-industry" (WE) effect in section 2.2 (see equation 4). In order words, we analyze the extent to which regions that have experienced large immigration of a particular type of labor have absorbed the increase in supply by employing that factor more intensively throughout all industries operating in the region, holding constant industry sizes at pre-immigration levels. Thus we now estimate regressions of the form shown in equation 5, but where the dependent variable is WE_{er}.

The results are displayed in table 7. The OLS specifications suggest large, significant within-industry effects. Changes in worker mix are estimated to have accommodated 36 to 55% of the changes in the potential labor force between 2001 and 2006. The IV

[23] Gandal, Hanson, and Slaughter (2005) test these effects in the context of immigration in Israel. They do not find support for Rybczinsky-type effects either.

specifications confirm that within-industry adjustments accounted for 34 to 54% of the inflows.

Table 8 shows the full decomposition (see equations 3 and 4) for the specification with 144 cells, unweigthed, with robust clustered standard errors. The IV results indicate that about 25% of the increase in the labor force induced by immigration was absorbed through non-employment, i.e. about a fourth of the additional potential workers remained non-employed. Since this figure is similar to the non-employment rate among the overall (pre-migration) population, this result is consistent with the inflow having no effect on overall employment rates.

Changes in industry mix across regions accounted for only 12% of the increase in potential workers (not significantly different from zero). Most of the increase (about 54%, or more than 70% of the employment adjustment) was absorbed through changes in worker mix in the existing industry structure, i.e. all industries using the more abundant type of labor more intensively. Finally, the remaining interaction effect accounted for the remaining 10% (not significant).

4. Conclusions

Spain has recently transitioned from a country of emigration to one of immigration. Since year 2000, Spanish regions have received very large immigration inflows. In 2006, 20% of the working-age population in the province of Madrid was foreign-born (16% in Barcelona), up from 9% (5%) in 2001. This large inflow was relatively unskilled compared with the native population.

We provide estimates of the causal effect of immigration on regional employment rates as well as on regional output mix and worker mix at the industry level. Methodologically, we follow a spatial correlations approach, exploiting regional variation in immigration flows. We also construct a Card-type instrument for changes in the composition of the labor force by region, using the exogenous variation given by historical settlement patterns of early immigrants.

We find that immigration has led to an increase in total employment, with practically no effect on employment to population ratios at the regional level. The increase in employment took place through a large effect on worker mix, i.e. the substitution of more educated workers for the now relatively more abundant less educated ones within industries. Immigration did not appear to have a significant effect on output mix, suggesting no Rybczinsky-type effects.

Overall, and despite the large differences in labor market institutions and the access of immigrants to public services, the channels of adjustment appear to have been surprisingly similar to those found for US metropolitan areas (Lewis, 2003). Mostly, all industries in each region have adapted their relative factor requirements to the changes in the skill composition of the local labor force.

Recent studies for the US (Lewis, 2003) and Germany (Dustmann and Glitz, 2007) using firm-level panel data suggest that the adjustment mechanism at work may involve firms in regions receiving the inflow of unskilled workers adopting production technologies that use that type of labor more intensively. Surely, further work is needed in order to understand the process of technology adoption following significant changes in the composition of local labor forces.

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Figure 1. Fraction of High School Dropouts by Region in 2006

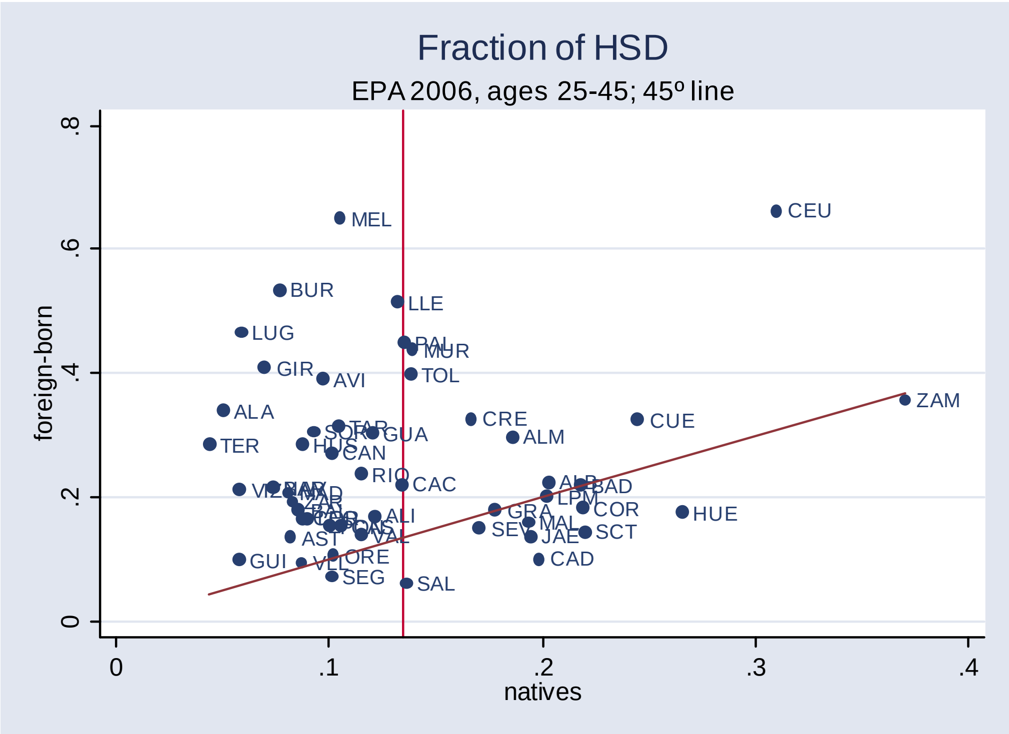

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
M_{er}	156	9507	20582	-1577	154994
$M_{er}/L_{er,2001}$	156	0,103	0,143	-0,327	1,025
Z_{er}	156	9507	22065	114	192139
$Z_{er}/L_{er,2001}$	156	0,109	0,165	0,010	1,634
$\%\Delta L_{er}$	156	0,064	0,428	-0,777	2,813
$\%\Delta N_{er}$	156	0,150	0,543	-0,784	4,585
$\%\Delta NR_{er}$	156	0,074	0,117	-0,474	0,578
UE_{er}	156	-0,051	0,145	-0,350	0,882
BE_{er}	156	0,137	0,111	-0,167	0,476
WE_{er}	156	-0,039	0,201	-0,587	0,456
IE_{er}	156	0,016	0,125	-0,324	1,335
BET_{er}	156	0,029	0,051	-0,166	0,165

Note: The number of observations corresponds to 52 regions times 3 education levels. All variables are constructed using 2001 and 2006 EPA data. The first four variables also use Census 2001 data, and the third and fourth also use the Census 1991. Details on variable definition and construction can be found in section 2.

Table 2. Actual and Imputed Migration Flows, 2001-2006

Country of origin	Coefficient	Stdev	
France	1,0915	(0,2020)	***
Italy	1,0338	(0,2691)	***
Portugal	0,6425	(0,1849)	***
UK	0,8942	(0,3083)	***
Germany	0,6636	(0,1477)	***
Other EU-12	0,9296	(0,3232)	***
Other Europe	0,5659	(0,0963)	***
Morocco	0,5594	(0,1258)	***
Other Africa	0,5743	(0,4893)	
USA	1,3272	(0,1435)	***
Cuba	0,8714	(0,1832)	***
Argentina	0,4635	(0,1348)	***
Venezuela	0,5424	(0,0848)	***
Mexico or Canada	1,3027	(0,0991)	***
Other Central Am. and Caribbean	0,3143	(0,1573)	**
Other South America	0,872	(0,0342)	***
Asia and Oceania	2,3373	(0,5296)	***
ALL COUNTRIES	0,7527	(0,0540)	***
N	156		

Note: Each coefficient is from a different regression. The dependent variable is the 2001-2006 migration inflow from each country of origin (M_{erc}), and the main explanatory variable is the imputed migration flow (Z_{erc}). The regressions also include region and education fixed effects. One asterisk indicates significance at the 90% confidence level, two indicate 95%, and three indicate 99%.

Table 3. First Stage Regression Results

	1		2		3		4		5		6	
Z_{er}	1,1956	***	1,5093	***	1,7671	***	2,8328	***	2,3868	***	2,3868	***
	(0,2757)		(0,3330)		(0,3533)		(0,5900)		(0,5259)		(0,7533)	
Educ 2	0,5303	***	0,58	***	0,5712	***	0,5618	***	0,5869	***	0,5869	***
	(0,0653)		(0,0484)		(0,0465)		(0,0471)		(0,0421)		(0,0699)	
Educ 3	0,5258	***	0,6001	***	0,5682	***	0,5313	***	0,5907	***	0,5907	***
	(0,0654)		(0,0545)		(0,0465)		(0,0480)		(0,0559)		(0,0593)	
Region f-e?	Y		Y		Y		Y		Y		Y	
Weights?	N		Y		N		N		Y		Y	
Drop small?	N		N		Y		Y		Y		Y	
Robust?	N		N		N		N		N		Y	
Cluster?	N		N		N		N		N		Y	
N	156		156		152		144		144		144	

Note: Each column reports the coefficients from a different regression. The dependent variable is the percent change in the population in each (r,e) cell, $\%\Delta L_{er}$. One asterisk indicates significance at the 90% confidence level, two indicate 95%, and three indicate 99%.

Table 4. Displacement Results

OLS	1		2		3		4		5		6	
M_{er}	1,4963	***	1,5911	***	1,4574	***	1,4243	***	1,5409	***	1,5409	***
	(0,2476)		(0,2140)		(0,1711)		(0,1637)		(0,1707)		(0,1077)	
IV												
M_{er}	.		5,8436	**	2,7549	***	1,7139	***	1,9161	***	1,9161	***
			(2,5193)		(0,5896)		(0,3007)		(0,3489)		(0,4113)	
t (1st st.)	0,28		1,93		3,88		6,38		5,57		5,57	
Region f-e?	Y		Y		Y		Y		Y		Y	
Educ. f-e?	Y		Y		Y		Y		Y		Y	
Weights?	N		Y		N		N		Y		Y	
Drop small?	N		N		Y		Y		Y		Y	
Robust?	N		N		N		N		N		Y	
Cluster?	N		N		N		N		N		Y	
N	156		156		152		144		144		144	

Note: Each cell reports the coefficient and standard error (in parenthesis) from a different regression. The dependent variable is the percent change in the population in each (r,e) cell, $\%\Delta L_{er}$. One asterisk indicates significance at the 90% confidence level, two indicate 95%, and three indicate 99%.

Table 5. Employment Results

OLS	1		2		3		4		5		6	
$\%\Delta L_{er}$	0,0892	***	0,0724	**	0,0702	*	0,1035	**	0,0766	*	0,0766	**
	(0,0302)		(0,0327)		(0,0400)		(0,0404)		(0,0394)		(0,0299)	
IV												
$\%\Delta L_{er}$	-0,1562		-0,0509		0,0037		0,2119	**	0,18	*	0,18	
	(0,0980)		(0,0849)		(0,0896)		(0,0937)		(0,0954)		(0,1428)	
Region f-e?	Y		Y		Y		Y		Y		Y	
Educ. f-e?	Y		Y		Y		Y		Y		Y	
Weights?	N		Y		N		N		Y		Y	
Drop small?	N		N		Y		Y		Y		Y	
Robust?	N		N		N		N		N		Y	
Cluster?	N		N		N		N		N		Y	
N	156		156		152		144		144		144	

Note: Each cell reports the coefficient and standard error (in parenthsis) from a different regression. The dependent variable is the percent change in the employment to population ratio in each (r,e) cell, $\%\Delta NR_{er}$. One asterisk indicates significance at the 90% confidence level, two indicate 95%, and three indicate 99%.

Table 6. Between-Industry Effects

All sectors	1		2		3		4		5		6	
OLS												
$\%\Delta L_{er}$	0,0684	***	0,0717	***	0,0947	***	0,0819	***	0,0815	***	0,075	***
	(0,0185)		(0,0196)		(0,0259)		(0,0240)		(0,0275)		(0,0248)	
IV												
$\%\Delta L_{er}$	0,1084	**	0,108	**	0,1288	**	0,1097	*	0,118		0,1039	
	(0,0477)		(0,0486)		(0,0577)		(0,0563)		(0,1251)		(0,0909)	
Only traded sectors												
OLS												
$\%\Delta L_{er}$	0,0066		0,01		0,0146		0,0136		0,0072		0,0081	
	(0,0083)		(0,0091)		(0,0119)		(0,0111)		(0,0081)		(0,0082)	
IV												
$\%\Delta L_{er}$	0,0366		0,0318		0,0374		0,0294		0,0351		0,0298	
	(0,0223)		(0,0227)		(0,0267)		(0,0263)		(0,0455)		(0,0383)	
Region f-e?	Y		Y		Y		Y		Y		Y	
Educ. f-e?	Y		Y		Y		Y		Y		Y	
Weights?	N		Y		N		Y		N		Y	
Drop small?	N		N		Y		Y		Y		Y	
Robust?	N		N		N		N		Y		Y	
Cluster?	N		N		N		N		Y		Y	
N	156		156		152		152		144		144	

Note: Each cell reports the coefficient and standard error (in parenthesis) from a different regression. The dependent variable is the percent change in the scale of each industry in a region, weighted by the initial employment level of the industry for a given education level as a share of the population in the region-education cell (BE_{er}). One asterisk indicates significance at the 90% confidence level, two indicate 95%, and three indicate 99%.

Table 7. Within-Industry Effects

All sectors	1		2		3		4		5		6	
OLS												
%ΔL_{er}	0,3634	***	0,4211	***	0,534	***	0,522	***	0,547	***	0,5285	***
	(0,0256)		(0,0265)		(0,0278)		(0,0271)		(0,0280)		(0,0219)	
IV												
%ΔL_{er}	0,34	***	0,379	***	0,5136	***	0,5106	***	0,5379	***	0,5217	***
	(0,0649)		(0,0652)		(0,0616)		(0,0633)		(0,0793)		(0,0620)	
Region f-e?	Y		Y		Y		Y		Y		Y	
Educ. f-e?	Y		Y		Y		Y		Y		Y	
Weights?	N		Y		N		Y		N		Y	
Drop small?	N		N		Y		Y		Y		Y	
Robust?	N		N		N		N		Y		Y	
Cluster?	N		N		N		N		Y		Y	
N	156		156		152		152		144		144	

Note: Each cell reports the coefficient and standard error (in parenthesis) from a different regression. The dependent variable is the percent change in the factor intensity of each industry in a region, weighted by the initial employment level of the industry for a given education level as a share of the population in the region-education cell (WE_{er}). One asterisk indicates significance at the 90% confidence level, two indicate 95%, and three indicate 99%.

Table 8. Summary of Non-Employment, Between and Within Effects

	Nonemployment (UE_{er})		Between (BE_{er})		Within (WE_{er})		Interaction (IE_{er})	
OLS								
Coeff.	0,2367	***	0,0815	***	0,547	***	0,1348	***
Stdev	(0,0320)		(0,0275)		(0,0283)		(0,0307)	
IV								
Coeff.	0,2453	***	0,118		0,5379	***	0,0988	
Stdev.	(0,0770)		(0,1251)		(0,0793)		(0,0982)	

Note: Each cell reports the coefficient and standard error (in parenthesis) from a different regression. The dependent variable is given in the column title. The reported coefficients are for the main explanatory variable, $\%\Delta L_{er}$. All specifications include region and education fixed effects, as well as robust standard errors clustered at the supra-regional level. The number of observations is 144 (very small cells have been dropped). One asterisk indicates significance at the 90% confidence level, two indicate 95%, and three indicate 99%.