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How do very open economies adjust to large immigration flows? Evidence from Spanish regions

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ABSTRACT

We study the labor market effects of the large immigration wave in Spain between 2001 and 2006. In this period the foreign-born share increased from 6% to 13%, with a total inflow exceeding three million immigrants. Our analysis exploits the large variation in the size of immigration flows across Spain's regions. To identify causal effects, we take advantage of the fact that immigrants' location choices were strongly driven by early migrant settlements that arrived during the 1980s. We find that the relatively unskilled migration inflows did not affect the wages or employment rates of unskilled workers in the receiving regions. The growth of the unskilled labor force was absorbed mostly through increases in total employment. This increase did not originate in changes in the composition of regional output, but was instead driven by changes in skill intensity at the industry level. Regions that received a large inflow of unskilled immigrants increased the intensity of use of the now more abundant (unskilled) labor, relative to other regions. The key industries responsible for this absorption were retail, construction, hotels and restaurants and domestic services. These results are inconsistent with standard open economy models but are in line with recent empirical studies for the United States and Germany.

1. Introduction

In recent years Spain received a massive wave of immigration, with the foreign-born share of total population jumping from 6% in 2001 to 13% in 2006.[1] This paper studies how Spanish regional economies responded to the large changes to the size and skill composition of their labor force caused by immigration. Specifically, we adopt a spatial correlations approach and employ instrumental variables to provide causal estimates of the effects of immigration on employment rates, wages, and the structure of production for Spanish provinces in the period 2001–2006.

Rising international migration flows over the last decade have revived interest on the economic effects of immigration, particularly in Europe.[2] The recent eastward enlargement of the European Union has sharply increased migration flows across its member states. Moreover, for countries such as Spain or Ireland, large-scale immigration is a completely new phenomenon in modern times, with important macroeconomic implications.[3]

The long history of immigration in the U.S. gave rise to a vast literature on the economics of immigration.[4] In contrast, relatively little is known about the effects of immigration in Europe and, in particular, regarding the new immigration countries. Given the large institutional differences between most European countries and the U.S. it is unclear how well the findings for the U.S. extrapolate to these countries.[5]

The Spanish immigration experience since year 2000 is particularly interesting for a number of reasons. First, the size of the inflows in absolute terms and relative to population has been spectacular. Except for Israel in the 1990s, no other OECD country has experienced such massive immigration flows in the postwar period. As noted earlier, the fraction of foreign-born individuals in the working-age population more than doubled in just 5 years, rising from 6% to 13% between 2001 and 2006 (see Fig. 1). During the same period, the foreign-born population in the U.S. went from 11 to 12.1%.[6]

Secondly, until recently Spain was a country of emigration. In modern times it is only during this period that immigrants started arriving in sizeable numbers. As a result, Spain's recent immigration

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[1] Local registry data at January 1st of each year. Population age 15–64.

[2] Chiswick and Hatton (2003).

[3] Bentolila et al. (2008) argue that Spain's recent immigration boom had important macroeconomic consequences. In particular, they argue it is crucial to understand the large drop in unemployment in a context of stable inflation.

[4] Important early contributions are Card (1990) and Borjas et al. (1996). Some recent important contributions include Borjas (2003), Ottaviano and Peri (2006), and Lewis (2003), among many others.

[5] A few influential studies are Hunt (1992) for France, Pischke and Velling (1997) for Germany, Dustmann et al (2005) and Manacorda et al. (2007) for the UK, and Carrasco et al. (2008) for Spain.

[6] U.S. Current Population Survey.

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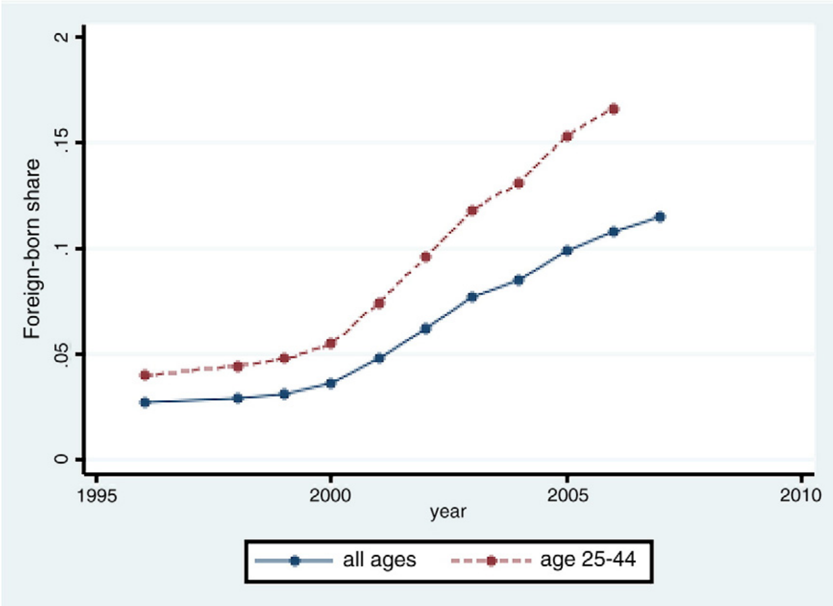

Fig. 1. Share of the foreign-born population relative to total population in Spain.
Source: Registry data at January 1st of each year ("Padrón").

surge was largely unexpected by economic agents. To the extent that the capital stock did not anticipate the immigration wave, we expect to observe negative short-run effects of immigration on wages. By the same argument, we also think it plausible to assume that the educational attainment of natives was not affected by the influx of immigrants in the short term.

Another feature of the Spanish experience is that a large fraction of recent immigrants are native Spanish speakers from Latin America. These special features make the Spanish immigration episode particularly interesting. Some researchers have already recognized this.[7]

We conduct a spatial correlations analysis focusing on regional economies.[8] Relative to countries, regions are very open economies, tightly interconnected by flows of factors, goods, and ideas. Consequently, absorption of immigration flows can operate through a variety of channels. In addition, the size of immigration flows relative to population is often orders of magnitude larger than for national economies.

This methodological approach seems well suited to the Spanish case. First, there is very large regional variation regarding the size of immigration flows. Fig. 2 reports the foreign-born share in 2006 (age group 25–45) for the 52 Spanish regions. While the provinces in the South and West of Spain are mostly below 6%, those around Madrid and on the Mediterranean display foreign-born shares around 20% and higher. Secondly, despite their low numbers, there is a relatively long history of migration to Spain from Morocco and several South American countries. As we shall show, the location choices of early arrivals partially determined the geographical distribution of recent immigrants. This provides us with a valuable source of exogenous variation in the size of immigration flows by region, which allows us to construct a credible instrument for the identification of the effects of interest.

The exercise we carry out in this paper is challenging in terms of data requirements. Our period of interest (2001–2006, roughly the period of the immigration surge) lies after the most recent Census year (2001), and thus we are restricted to the smaller samples available from the Labor Force Survey. In many countries these data are too sparse to accurately quantify changes in the foreign-born population at the regional level. However, this problem is much less serious in the case of Spain. The reason is that high-quality registry data exist that accurately track changes in the (both native and foreign-born) population at the local level. These data are an important input into the sampling design of the Spanish Labor Force Survey.[9]

Our main results are the following. First, we document that immigration flows were relatively unskilled and analyze their effect on aggregate labor market outcomes. We find that immigration did not have any significant impact on the structure of wages or on employment rates in Spanish regional labor markets. This finding is consistent with several prior studies using data for other countries.[10]

The recurrent finding of insensitivity of wages to immigration flows has led researchers to explore alternative mechanisms by which economies can absorb immigration flows. Recognizing that regional and local economies are highly interconnected by trade, empirical work has focused on the adjustment mechanism described by the Rybczynski theorem.[11] According to this celebrated result, in response to an inflow of a factor of production, a small open economy may not suffer any changes to equilibrium factor prices and absorb the inflow simply by changing its structure of production. Specifically, production (and employment) would expand in sectors that use that factor intensively. The pioneering empirical explorations of this result are Hanson and Slaughter (2002) and Gandal et al. (2005), who carry out accounting decompositions. We follow the more recent approach developed by Lewis (2003), which uses the spatial correlations methodology to provide a more formal econometric test of the Rybczynski theorem based on a between-within industry decomposition. In a study contemporaneous to ours, Dustmann and Glitz (2008) apply Lewis' approach using German data.

We find that immigration did not significantly change regional output mix (between-industry absorption). Instead, the main channel

[7] See, for instance, Carrasco et al. (2008) and Amuedo-Dorantes and De la Rica (2007, 2008).

[8] The spatial correlations approach was pioneered by Altonji and Card (1991), and has been widely used since then. See for example Ottaviano and Peri (2006), Dustmann and Glitz (2008) and Saiz (2007).

[9] More details are provided in the data in Appendix A.

[10] See the surveys in Borjas (1994), Friedberg and Hunt (1995) and Card (2005).

[11] Rybczynski (1955).

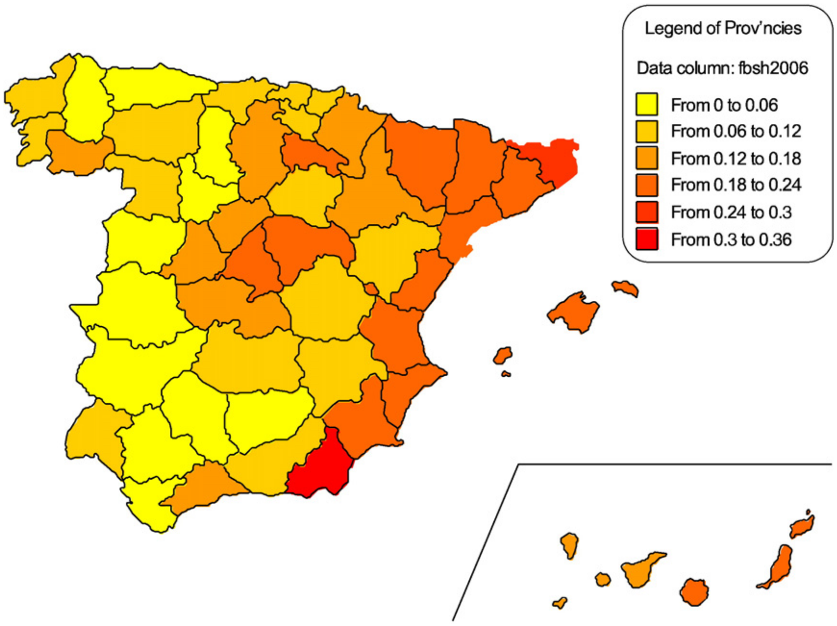

Fig. 2. Foreign-born share in 2006 (age bracket 25–45) in Spanish provinces.
Source: 2006 Spanish Labor Force Survey (EPA).

of absorption of immigration-driven increases in labor supply was within-industry. In other words, following a relatively unskilled labor inflow, the typical industry in the receiving regions increased the intensity of use of this type of labor, relative to regions without immigration.

Lastly, we analyze the role played by individual industries in the absorption process. We find that the industries that played the leading role are largely non-tradable: retail, hotels and restaurants, construction and domestic services.

Our findings imply that the adjustment of Spanish regional economies to immigration shocks is very similar to the patterns found in the U.S. and in Germany. Moreover, our results reinforce the view that standard open-economy models are not able to account for the response of local and regional economies to factor supply shocks. In particular, we do not find the strong connection between relative factor intensities and relative factor prices implied by the theory. Finally, our results also contribute to the literature on the effects of the recent wave of immigration in Spain. Unlike previous work, our analysis uses the recently available new wage data based on Social Security records. In addition, we are the first to show that a Card-type instrument is useful also for Spain to identify the causal labor market effects of immigration.

We are not the first to analyze the economic effects of immigration in Spain. Carrasco et al. (2008) use data for the period 1991–2001 from a variety of sources. Methodologically they follow the skill correlations approach introduced in Borjas (2003), adapted to the data availability for Spain. Their main finding is that growth in the foreign-born share across skill cells is negatively correlated with growth in employment rates and wages. However, the magnitudes are small and the effects not robust. The authors conclude that there is no robust evidence of negative labor market effects of immigration. In comparison, our period of interest is 2001–2006, corresponding to much larger inflows, and we use different data sources as well as a different methodology (spatial correlations). Also, in addition to studying wage and employment effects, we focus on the effects of immigration on industrial composition at the regional level.

Amuedo-Dorantes and De la Rica (2007) estimate the immigration surplus, both at the national and regional levels in Spain. Amuedo-Dorantes and De la Rica (2008) show that immigration led Spain-born workers to shift occupations, toward less exposed, more communication-intensive occupations. Also related to this study, Blanes et al. (2008) analyze the effects of immigration on the industry structure of Spanish regions. Their data is for the period 1995–2002, prior to the largest inflows, and their methodology is an accounting decomposition as in Hanson and Slaughter (2002).

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework. Section 3 describes the data sources and introduces the empirical strategy. Section 4 presents the results of the empirical analysis, starting with the effects of immigration on wages and employment and moving on to the between and within industry absorption. Section 5 concludes.

2. Theoretical framework

2.1. A multi-sector economy

Our setup is a version of the small open economy model often used in the labor and empirical trade literatures.[12] We view each province as a small open economy.[13] There are J final goods (sectors), produced using three types of labor, differentiated by skill levels (defined by education). We follow the usual small open economy setup, where labor markets are assumed to be local, whereas final goods markets are global and trade is costless.

In the Heckscher–Ohlin tradition, we assume that natives and immigrants with the same education level are perfect substitutes. Recently, Ottaviano and Peri (2006, 2008) provide estimates of the degree of substitution between native and foreign-born workers within narrowly defined age and education cells, using US Census data. Their results point to a high elasticity of substitution, but well short of infinity. There are reasons to believe that there may be a larger degree of substitution between natives and immigrants in Spain than in the US. The reason is that a large fraction of recent immigrants in Spain are native Spanish speakers (more than 40%), and many others have mother tongues that are relatively close to Spanish (e.g. Romanians). As a result, native workers may have a

[12] Leamer (1995), Hanson and Slaughter (2002) and Gandal et al. (2005).
[13] We use the terms “province” and “region” interchangeably throughout the paper.

smaller comparative advantage in language-intensive tasks in Spain than in the US.[14] In order to derive our econometric specifications as simply as possible, we proceed under the assumption of perfect substitution. We shall later discuss how relaxing this assumption might affect our results.

Let (L_1, L_2, L_3) denote the economy's endowment of workers by skill type, and let N_e^j be the number of workers with skill level $e=1$, 2, 3, employed in the production of final good j. We assume that all sectors have constant returns to scale in the three labor inputs[15]:

$$y^j = f^j\left(N_1^j, N_2^j, N_3^j\right) = N^j f^j\left(\lambda_1^j, \lambda_2^j, \lambda_3^j\right), \tag{1}$$

where N^j denotes total employment in sector j, and λ_e^j is the fraction of e-type employment in that sector. Note that technologies are allowed to differ across sectors but are identical across all regions. We also assume that some workers are not employable. As a result, the total population with a given education level can be written as the sum of the unemployed (unproductive workers) plus employment in all sectors. That is, for each skill $e=1$, 2, 3, we have

$$L_e = U_e + \sum_{j=1}^{J} \lambda_e^j N^j \tag{2}$$

2.2. A useful accounting identity

Our goal is to estimate the effects of (migration-driven) shocks to a region's labor endowments on the industry structure of employment. Following Lewis (2003), the percent increase in the size of an education group can be decomposed into the (weighted) sum of the percentage increases in the employed and the non-employed population:

$$\frac{\Delta L_e}{L_{e,0}} = \%\Delta L_e = \frac{N_{e,0}}{L_{e,0}}[\%\Delta N_e] + \frac{U_{e,0}}{L_{e,0}}[\%\Delta U_e], \tag{3}$$

where 0 is the initial period and Δ denotes the change from period 0 to 1 (in our application, from 2001 to 2006).

Let us now disaggregate employment by sector. Consider an inflow of unskilled workers into a region, with no changes in the size of the other skill groups. Some of the new workers may be unproductive and will become unemployed. The rest will be absorbed through an increase in the aggregate employment of unskilled workers in the economy. This expansion in unskilled employment can be due to: a) an increase in the scale of production in some industries, at unchanged skill intensities ("between-industry" absorption), b) an increase in the intensity of use of unskilled labor, given the output mix ("within-industry" absorption), and c) an increase in unskilled employment arising from changes in both the scale of production and the intensity of use of unskilled labor.

More generally, consider a change in a region's skill endowments between periods 0 and 1: ($\%\Delta L_1$, $\%\Delta L_2$, $\%\Delta L_3$). Intuitively, these increases in the workforce will be absorbed through one or several of the following routes. First, some of the new workers may simply stay unemployed. Second, each industry may adjust its level of production and employment while keeping relative factor intensities unchanged. Third, relative factor intensities may change, without affecting the overall composition of output in the region.

After a bit of algebra Eq. (3) delivers the following accounting identity. For each education group $e=1$, 2, 3, an economy-wide increase in the size of the group can be decomposed into non-employment (UE), a purely between-industry adjustment (B), a purely within-industry adjustment (W), and an interaction term (I). Formally,

$$\begin{aligned}\%\Delta L_e &= UE_e + [B_e + W_e + I_e] \\ &= \left(1-\sigma_{e,0}\right)[\%\Delta U_e] + \sum_j \sigma_{e,0}^j\left[\%\Delta N^j\right] + \sum_j \sigma_{e,0}^j\left[\%\Delta\lambda_e^j\right] \\ &\quad + \sum_j \sigma_{e,0}^j\left[\%\Delta N^j\right]\left[\%\Delta\lambda_e^j\right]\end{aligned} \tag{4}$$

where $\sigma_{0,e}^j$ is the initial share of sector j's employment in the total population with education level e, and $\sigma_{0,e}$ is the employment–population ratio for education level e:

$$\sigma_{e,0}^j = \frac{N_{e,0}^j}{L_{e,0}}, \quad \lambda_e^j = \frac{N_e^j}{N^j}, \quad \sigma_{e,0} = \sum\nolimits_j \sigma_{e,0}^j.$$

In words, the between-industry adjustment term B_e is a weighted sum of the percentage increase in the size of each industry, where the weights capture each industry's relative size in employing each skill type in the initial year. Similarly, the within-industry adjustment term W_e is a weighted sum across all industries of the percentage change in the share of workers with skill type e employed in each industry. We note that this is the only channel of adjustment operating in one-sector models: increases in the supply of, say, unskilled labor lead to a more unskilled-intensive production of the economy's output. Of course, the price of unskilled labor relative to other factors of production has to fall to induce optimizing firms to move along the isoquant. In our multi-industry framework, it is still true that changes in relative factor intensities at the industry level are intimately related to changes in relative factor prices.

We can now derive a test for Rybczynski effects using this decomposition. The Rybczynski theorem states that, under certain conditions, an exogenous increase in the size of a skill group in the economy will be absorbed through a change in the sector distribution of output (and employment) in the economy, with no changes in relative factor intensities in any sector or in equilibrium wages. Intuitively, output (and employment) would increase in the industries using that factor intensively, which would then export it to other regions (or countries) embodied in their output. In terms of our previous decomposition, the Rybczynski theorem implies that: $\%\Delta L_e = UE_e + B_e$, since relative factor intensities remain constant in all industries.[16]

3. Data and empirical strategy

3.1. Data sources

Our two main sources of data are the Spanish Labor Force Survey (LFS) and the Continuous Sample of Working Lives (CSWL), a recently available large sample of Social Security records. We also make use of the 1991 Census to build our instrument.

We use the four quarters of the 2001 and 2006 LFS. This is the best data source available containing the relevant variables over our period of interest, given that the most recent Census year is 2001. The Spanish LFS does not contain information on wages or income.

[14] For evidence on the degree of substitution between natives and immigrants based on occupation-switching, see Peri and Sparber (2008) for the US and Amuedo-Dorantes and De la Rica (2008) for Spain.

[15] Alternatively, this can be interpreted as goods being produced using the three types of labor plus physical capital, and each region faces a perfectly elastic supply of capital. Production displays decreasing returns to scale in the labor inputs, but constant returns to scale in all four inputs. Our technology with constant returns to scale in the labor inputs can be seen as a reduced form for this environment. Our empirical model will also impose constant elasticity of substitution across all education groups.

[16] In the standard rendition of the theorem all workers are productive and hence the unemployment term is zero. In any case, all of the increase in employment is due to the between-industry component.

However, it has some advantages relative to the CPS in the US. Not only does it have a larger sample size, but its sampling is designed based on local population registry data, which is a reliable, up-to-date source that ensures that the sample is representative at the regional level, as well an accurate tracking of the size of the foreign-born population (see Appendix A for more details).

We obtain detailed individual-level information from the LFS on province of residence, educational attainment, age, country of birth, and employment by industry.[17] We use a 2-digit industry classification, which leads to 30 industries. Throughout the paper, we define immigrants as foreign-born workers. We define three education levels: high-school dropouts (HSD), high-school graduates (HSG), and individuals with completed university studies (COG). Appendix A provides further details on the exact definition of the education groups. All variables in the analysis except wages and (partially) the instrument are constructed from LFS data.[18]

For our wage data, we use the recently available 2006 Continuous Sample of Working Lives (CSWL). This is a large representative sample from the Social Security registry. For 4% of all individuals in the Social Security accounts in a given year (both employed and unemployed), the dataset provides a full account of their working histories. Specifically, it provides individual data on salaries and working days, for every year since the individual first obtained a Social Security number. The dataset provides information on individual characteristics, such as age, gender, and education. It also provides characteristics of the employer, such as its geographical location, and of the particular employer–employee relationship. Namely, it reports the worker's category,[19] his full-time or part-time status, and whether he is self-employed. We focus on daily wages (as in Lacuesta et al. 2009) for full-time, year-round workers, excluding the self-employed, following the standards in much of the literature on wages. Our sample contains 147,854 individuals in year 2001 and 139,179 in 2006.

There are two important limitations of this data set. The first is that annual salaries are severely bottom and top coded. The nature of bottom (top) coding in our data is the following. All employers are required to pay a fraction of their workers' annual salary as Social Security contributions. Below (above) a given annual salary, employers are forced to pay a fixed amount, and not a percentage of the actual salary received by the employee. For these workers, the CSWL does not report the actual salary, but the administratively set level that is used to compute the minimum (maximum) contribution. The second limitation is that the education data reported in the CSWL is based on local registry data, and these education records are not updated regularly.

We deal with the first problem by using median instead of mean values to estimate province-education wages, which is the crucial data input in our wage regressions. To address the second shortcoming, we amend the education variable by combining it with the information on worker category provided by the CSWL. We provide the details in Appendix A. Furthermore, we exploit the number of bottom-coded individuals as an additional outcome to evaluate the effects of unskilled immigration at the lower end of the wage distribution.

To build our instrument, we combine data from the LFS and the 1991 Census. In particular, we use the LFS to compute the Spain-wide inflows of foreign-born workers in the 2001–2006 period. The 1991 Census is used to calculate the geographical distribution of the 1991 stock of immigrants (by country of birth) across Spanish provinces.

Table 1
Descriptive statistics, 2001–2006.
Data sources: LFS 2001 and 2006 (all quarters), Census 1991 (for the construction of the instrument, Z), and 2006 MCVL (for wages).

Variable	Obs	Mean	Std. dev.	Min	Max
All					
Population % change ($\%\Delta L_{e,r}$)	156	0.1572	0.2404	−0.3640	1.0743
Migration inflow ($M_{e,r}/L_{e,r,2001}$)	156	0.0942	0.0918	0	0.5947
Imputed inflow ($Z_{e,r}/L_{e,r,2001}$)	156	0.0986	0.1155	0.0081	1.0165
Percent change in emp. ($\%\Delta N_{e,r}$)	156	0.2435	0.2662	−0.3015	12,672
Change in emp. rate ($\Delta NR_{e,r}$)	156	0.0517	0.0381	−0.0706	0.1600
Percent change in wages ($\Delta \ln w_{e,r}$)	156	0.2739	0.0438	0.1946	0.4682
Between-industry absorption ($B_{e,r}$)	156	0.1414	0.1030	−0.1158	0.4468
Within-industry absorption ($W_{e,r}$)	156	0.0225	0.1233	−0.2688	0.4147
Absorption interaction ($I_{e,r}$)	156	0.0183	0.0462	−0.0939	0.2278
Non-employment absorption ($U_{e,r}$)	156	−0.0260	0.0616	−0.1746	0.1582
High school dropouts					
Population % change ($\%\Delta L_{e,r}$)	52	−0.0510	0.1409	−0.3640	0.4260
Migration inflow ($M_{e,r}/L_{e,r,2001}$)	52	0.0759	0.0602	0.0063	0.317
Change in emp. rate ($\Delta NR_{e,r}$)	52	0.0491	0.0316	−0.0194	0.1228
Change in log wages ($\Delta \ln w_{e,r}$)	52	0.2948	0.0519	0.2113	0.4682
High school graduates					
Population % change ($\%\Delta L_{e,r}$)	52	0.2979	0.2212	−0.1433	1.0743
Migration inflow ($M_{e,r}/L_{e,r,2001}$)	52	0.1333	0.1259	0	0.5947
Change in emp. rate ($\Delta NR_{e,r}$)	52	0.0556	0.0369	−0.0131	0.16
Change in log wages ($\Delta \ln w_{e,r}$)	52	0.2657	0.0286	0.2156	0.3580
College graduates					
Population % change ($\%\Delta L_{e,r}$)	52	0.2246	0.1947	−0.2746	0.6600
Migration inflow ($M_{e,r}/L_{e,r,2001}$)	52	0.0735	0.0619	0.006	0.3228
Change in emp. rate ($\Delta NR_{e,r}$)	52	0.0505	0.0451	−0.0706	0.1224
Change in log wages ($\Delta \ln w_{e,r}$)	52	0.2612	0.0404	0.1946	0.3849

Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e), thus $N = 52 \times 3 = 156$. See Appendix A for the definition of education levels.

We restrict the analysis to population in the age group 25 to 45 in order to minimize age composition effects. This age group contains the bulk of the working-age, foreign-born inflows during the period.[20] However, for the sake of generality we also re-estimate all models for the broader age range of 25 to 54.

Our final dataset aggregates individual-level data to province-education cells. Since we have 3 education groups and 52 provinces, the total number of education-province cells is 156. Table 1 summarizes the main variables we employ in the analysis, which we discuss in Section 4.[21]

3.2. Empirical strategy

The core of our analysis is the estimation of a series of econometric models that share the same right-hand side variables but differ in their dependent variable. For each dependent variable Y, we estimate a regression of the following form:

$$Y_{e,r} = \beta\left(\%\Delta L_{e,r}\right) + \alpha_e + \mu_r + \varepsilon_{\varepsilon,r}. \tag{5}$$

We start by using changes in log wages and employment rates as our dependent variables, and later move on to estimating between and within industry absorption regressions. In all cases, the main regressor is the percentage increase in the size of a skill group in the

[17] The sample size is 208,841 individual observations for 2001 and 192,803 for 2006.
[18] One concern is whether the undocumented foreign-born population is appropriately captured by the LFS. While most likely some of them are not being reached by the survey, we suspect that this data problem is less of a concern in the case of Spain than in some other countries. Our conjecture is based on the existence of the local Population Registry, an important source of data that is used in the design of the LFS. For more details, see Appendix A.
[19] In Spanish, worker category corresponds to "grupo de cotización".
[20] In 2006, almost 73% of all immigrants and 80% of all working-age immigrants were between 25 and 45 years old. In comparison, 66% of working-age natives were in age group 25–45.
[21] See the appendix for the number of individual observations in each cell and details on the aggregation procedure.

region, $\%\Delta L_{e,r}$. The main coefficient of interest, β, should be interpreted as the effect of a 1% increase in the size of skill group e in region r on each dependent variable, for instance, the percentage change in wages for that skill group in the region. We allow the slope coefficient β to vary across models, however we impose symmetric values across regions and education levels.[22]

Our specifications include education and region fixed effects (α_e and μ_r, respectively). The region fixed effects capture any regional differences in the business cycle or labor demand that are common to all education groups. For example, we are allowing for differences in regional growth rates for total factor productivity. The education fixed effects control for global changes in the relative demand for each type of labor, for instance due to skill-biased technical change, as well as for nation-wide changes in the relative supply of each skill group. We estimate all regressions either with robust standard errors or using weights.[23]

Another potential adjustment channel to migration inflows is native displacement, as has been recognized in the literature (Card and DiNardo, 2000). Instead of estimating displacement effects directly, our approach is to use as our main explanatory variable the total size of the labor force by education (including both immigrants and natives), rather than just the foreign-born inflows. This is also the approach in Lewis (2003).

We first estimate the effect of immigration on wages and employment rates. Following Card (2001) and Lewis (2003), our dependent variables are the change in the employment rate of a given education group ($\Delta NR_{e,r}$) and the log change in the wage of that group ($\Delta \ln w_{e,r}$). Potentially immigration shocks that alter the skill distribution also affect relative wages. In this case, the one-sector model would accurately account for the effects of an immigration shock. However, at least for the US, there is a large consensus that immigration has at most a very small impact on the regional wage structure.

Open economies have alternative channels of adjustment to shocks to their factor supplies. Since Hanson and Slaughter (2002), several authors have examined the role of Rybczynski-type effects in the absorption of immigration shocks. In order to test for this adjustment, we estimate the effects of the immigration shock on the structure of production of Spanish regions. We attempt to explain what fraction of the changes in the size of a skill group in a region has been absorbed by a i) increases in non-employment (UE), ii) between-industry changes in employment (B), iii) within-industry changes in employment (W), and iv) an interaction of the latter two channels (I), as defined in Eq. (4). According to the Rybczynski theorem, the full adjustment will take place through between-industry changes and, possibly, changes in unemployment. In terms of Eq. (4):

$$\%\Delta L_e = B_e + UE_e$$

$$W_e + I_e = 0.$$

Even though we have addressed the issue of unobserved heterogeneity across regions and education groups through the inclusion of the respective fixed effects, our estimates may still be corrupted by spurious correlations arising from the endogeneity of immigrants' (and natives') location choices. More specifically, it may be the case that immigrants with a particular skill choose to locate in provinces that display high growth in the demand for that skill during the 2001–2006 period, unobserved by the econometrician.

We follow Lewis (2003) and adopt an instrumental variables approach inspired in Card (2001).[24] Our aim is to build a variable that is correlated with changes in a region's skill composition over the period 2001–2006, but is uncorrelated with current shocks to the region's demand for that type of labor. We base our instrument on a robust feature of immigration flows, the importance of migrant networks. Immigrants tend to locate in areas with existing clusters of immigrants from their same country of origin. While this type of instrument has been widely used to study the effects of immigration in the US, we are the first to apply it to the case of Spain.

More specifically, let $M^{Sp}_{e,c}$ (2001–2006) denote the Spain-wide inflows during the period 2001–2006 of immigrants from country of origin c and education level e. We "assign" these individuals to Spanish provinces using the cross-sectional distribution of immigrants in 1991 for each country of origin. These distributions are the result of immigration waves that occurred during the 1980s.

Let $\pi_{r,c}$ (1991) denote the share of all immigrants born in country c living in Spain in 1991 that were located in province r. We build the imputed 2001–2006 inflow from country c with education e into province r by assigning Spain-wide inflows using 1991 weights, and denote it by $Z_{e,r,c}$. Our instrument $Z_{e,r}$ is the sum over all countries of origin:

$$Z_{e,r} = \sum_{c=1}^{C} Z_{e,r,c} = \sum_{c=1}^{C} \pi_{r,c}(1991)\, M^{Sp}_{e,c}(2001\text{–}2006) \tag{6}$$

The first-stage regressions in the next section examine the relevance of our instrument for the Spanish case. We now briefly discuss the assumption of exogeneity. Changes in a region's total population of workers with a given skill level are the sum of changes in the native and foreign-born populations. Our instrument is a predictor of the changes in the supply of skill arising from foreign-born inflows. Our identifying assumption is that the location decisions of immigrants by country of origin in the 1980s are not related to the 2001–2006 changes in our outcomes of interest, namely, wage growth and the structure of employment by education level. We believe the lag of more than 10 years that we use is sufficiently long for our identifying assumption to hold.

In addition, we can analyze the location patterns of early immigrant groups and see if they are plausibly uncorrelated with more recent (changes in) regional labor market conditions. The strength of the instrument turns out to be driven by South American and Moroccan immigrants (who were among the top source countries both in 1991 and in the 2000s). In 1991, these two groups had very distinct geographic distributions. Although Madrid and Barcelona had important immigrant clusters from all source countries, there were important Moroccan settlements in the South-Eastern coast (Málaga, Alicante, etc), most likely related to geographic proximity to Morocco. South Americans, on the other hand, clustered disproportionately in the Canary Islands and the North-East (Galicia), regions that sent large numbers of emigrants to South America in the early 20th century. This suggests that recent inflows may be descendants of Spanish emigrants or their relatives. These patterns, in turn, suggest that non-economic reasons were important determinants of the location of early immigrant settlements within Spain, thus lending support to the exogeneity of our instrument.

4. Results

4.1. Descriptive statistics

During the period 2001–2006, population growth in Spain's provinces was fuelled mainly by immigration. In the average province the 25 to 45-year-old population grew by 10%, with 90% of the growth being attributable to inflows of foreign-born (local population registry). In 2006, the top countries of origin were Ecuador (16% of all immigrants 25–45), Morocco (13%) and Romania (10%), followed by Colombia and Argentina. Forty-seven percent of all immigrants in the 25–45 age group were Latin-American, while 18% were African.

[22] These restrictions are consistent with CES sector-specific production functions.

[23] We weigh each cell by $((L^{(-1)}_{r,2001}) + (L^{(-1)}_{r,2006}))^{(-0.5)}$, as in Lewis (2003).

[24] Ottaviano and Peri (2006) and Saiz (2007), among others, have also used this type of instrument for the US.

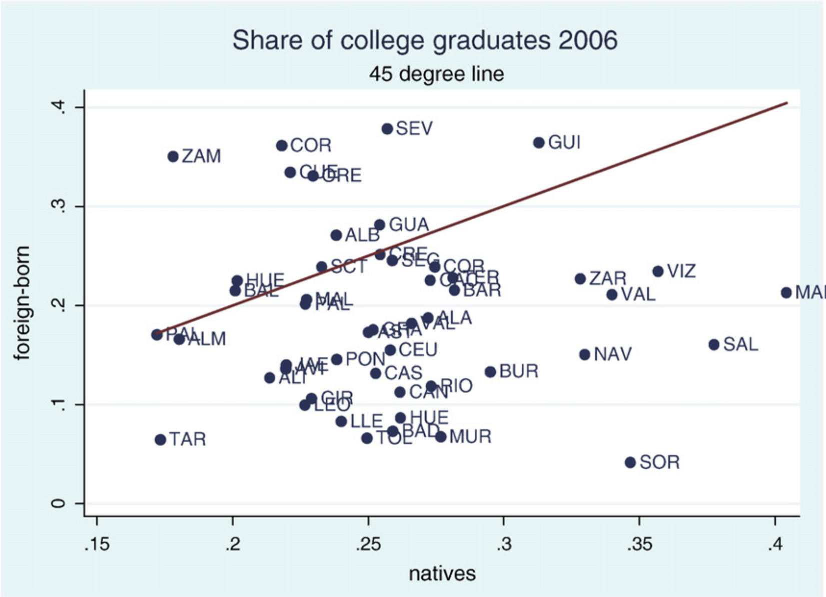

Fig. 3. Fraction of college graduates among native and foreign-born population, year 2006. Notes: The vertical axis is the share of college graduates among the foreign-born population. The horizontal axis is the analogous share but for the native-born population.
Source: 2006 LFS, second quarter.

We now inspect in greater detail the changes in Spanish regional labor markets during this period. As noted earlier, our regional units of analysis are the 52 Spanish provinces. The size of the labor force in the average province was almost 350,000 individuals in year 2001 (LFS, age group 16–64).[25] Table 1 reports some descriptive statistics. Our figures refer to individuals age 25–45. The average increase in the size of education-province cells between 2001 and 2006 was roughly 16%, ranging from a sharp drop of 36% to a spectacular increase of 107%.[26] Inflows of foreign-born workers accounted for a large fraction of the increase, with the average cell receiving a migrant inflow as large as 9% of the initial cell size, and up to 59%.

This period also witnessed important changes in the skill distribution of the Spanish labor force. While on average the HSD group shrank down by 5%, the numbers of HSG and COG increased by 30% and 22%, respectively. Namely, Spanish provinces experienced a substantial increase in the relative supply of skilled labor between 2001 and 2006.

In this context of rapid cohort skill upgrading, immigration flows were relatively unskilled. While on average the 2001–2006 inflows of foreign-born workers increased the size of the COG population by 7%, they led to increases of 8% and 13% in the HSD and HSG populations, respectively. In other words, in the absence of immigration, the increase in the relative supply of skills would have been even more dramatic.[27]

As noted in the Introduction, another salient feature of the recent Spanish immigration experience is its highly unequal regional impact. Even more relevant for our purposes, the skill composition of the inflows of foreign-born workers also varied across regions. Fig. 3 reports the skill distributions of the native and immigrant population in 2006. Specifically, it plots the fraction of college graduates among natives and among immigrants for each province. Clearly, most provinces lie below the 45° line. That is, the fraction of college graduates among the foreign-born population is lower than for natives in most regions. It turns out that the provinces that received large inflows are also those for which immigrants were relatively more unskilled. As a result, wherever inflows were large, immigration led to a significant increase in the relative supply of unskilled labor. Finally, the figure also reveals the large variation in the skill composition of immigration flows across provinces. While for some provinces only 5% of immigrants held a college degree, for others it was close to 35%.

4.2. Instrument relevance

Let us here examine whether our instrument is able to predict actual changes in regional skill supplies. We proceed in two steps. First, we examine if the instrument is correlated with increases in the actual foreign-born population. Secondly, we check that it is also correlated with total changes in region-education cells, which include both natives and foreign-born workers. The latter is the first-stage regression of our two-stage least-squares estimates.

This type of instrument has been used often for the US, a country with a long history of immigration. Beforehand it is unclear whether the instrument will have predictive power in the case of Spain, where immigration only started timidly during the second half of the 1980s and accelerated over the course of the 1990s.

Table 2 reports a series of regressions where imputed inflows are used to explain actual inflows by country of origin. Most coefficients are highly significant. More importantly, imputed inflows predict well actual flows for the main source countries (Morocco, Argentina and other South American countries). The last row of the table, "All countries", shows that the instrument $Z_{e,r}$ helps explain the total actual inflows of foreign-born workers into Spanish regions. Columns 1 and 2 show that the relationship holds both in levels and relative to the initial size of skill groups.

More crucial for our analysis, we next examine whether our instrument is capable of explaining actual changes in regional skill supplies, which are the sum of the foreign-born inflows and the

[25] Provinces Ceuta and Melilla (located on the African continent) are substantially smaller than the rest, with 2001 labor forces equal to 26 and 23 thousand, respectively. In our regression tables we always include a set of estimates where these two provinces are excluded from the sample.

[26] The changes reported in the table may appear "too large" for some observations. One should keep in mind that they refer to a subgroup of the population (age 25–45) and that a few provinces are very small. At any rate, even our more extreme observations are in sync with other studies (see, for example, IVIE 2007).

[27] The Labor Force Survey allows for disaggregating education levels further. Immigrants are heavily over-represented in the lowest education category (no primary school degree). In other words, our 3-skill classification underestimates the increase in the supply of unskilled workers due to immigration.

Table 2
Regression results, actual and imputed immigration flows by education and province. Data sources: 2001 and 2006 LFS, and 1991 Census.

	1		2	
Dependent variable	Migration inflow ($M_{e,r}$)		Migration inflow per population ($M_{e,r}/L_{e,r,2001}$)	
Main explanatory variable	Imputed inflow ($Z_{e,r}$)		Imputed inflow per population ($Z_{e,r}/L_{e,r,2001}$)	
Country of origin	Coefficient	(s.e.)	Coefficient	(s.e.)
France	1.4975	(0.2190)***	0.6098	(0.3995)
Italy	0.6475	(0.5043)	0.7254	(0.4377)
Portugal	−0.4536	(0.2744)	0.0899	(0.2278)
UK	0.6837	(0.5827)	0.6841	(0.1661)***
Germany	0.6311	(0.4870)	0.7531	(0.4195)*
Other EU-12	1.5578	(0.2796)***	1.3007	(0.2018)***
Other Europe	0.8659	(0.1230)***	−0.0773	(0.1531)
Morocco	0.7340	(0.1048)***	0.0671	(0.0260)**
Other Africa	0.2610	(0.0583)***	0.1672	(0.3217)
USA	0.5655	(0.1692)***	−0.1482	(0.4917)
Cuba	1.3397	(0.2001)***	0.3902	(0.1394)***
Argentina	0.6485	(0.1424)***	0.6364	(0.1954)***
Venezuela	−0.1363	(0.2226)	0.0717	(0.0809)
Mexico or Canada	2.0507	(0.0761)***	0.0346	(0.0966)
Other Central Am. and Caribbean	0.4761	(0.0800)***	0.4611	(0.4241)
Other South America	0.7655	(0.0384)***	0.5886	(0.1700)***
Asia and Oceania	1.1115	(0.0760)***	0.3357	(0.3357)
All countries	0.6180	(0.0537)***	0.3178	(0.0968)***

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each row reports the coefficient from a separate regression, where the dependent variable is the actual migration inflow from a given country of origin, and the explanatory variable is the "imputed" inflow (Z, defined in Section 3.2, Eq. (6)). Standard errors are shown in parenthesis. All regressions include region and education fixed-effects and use weights. The number of observations is 156. The weights used are $((L_{r,2001}^{(-1)})+(L_{r,2006}^{(-1)}))^{(-0.5)}$.

changes in the native population. This is our first-stage regression. The dependent variable is the percentage change in the actual size of a region's skill group. The main regressor is $Z_{e,r}$ divided by $L_{e,r}^{2001}$, that is, the imputed inflow relative to the total 2001 size of that skill group in the region. Specifically, we estimate

$$\frac{\Delta L_{e,r}}{L_{e,r}^{2001}}=\delta\frac{Z_{e,r}}{L_{e,r}^{2001}}+\alpha_e+\mu_r+\varepsilon_{e,r}. \tag{7}$$

Table 3 reports OLS estimates of this relationship. The first column uses robust standard errors, and in addition, column 2 excludes two very small provinces that could be considered outliers.[28] Finally, column 3 uses weights and constitutes our preferred specification. The use of efficient weights corrects for the potential heteroskedasticity, and this specification also facilitates the comparison of the results with Lewis (2003).

Across all specifications, the coefficient is highly significant and close to one, as one would expect based on the definition of the instrument.[29] In our preferred specification the F-statistic associated with the instrument takes a value of 12. Thus, we conclude that the instrument is valid for the case of Spain, a country with a relatively recent immigration history.[30]

Table 3
First-stage regressions.
Data sources: 2001 and 2006 LFS, and 1991 Census.

Dependent variable: Population percent change (%$\Delta L_{e,r}$)			
	1	2	3
Imputed migration inflow ($Z_{e,r}/L_{e,r,2001}$)	0.7142**	1.1268**	0.8975***
	(0.3319)	(0.5001)	(0.2592)
High school grads.	0.3205***	0.3069***	0.3334***
	(0.0330)	(0.0345)	(0.0324)
College grads.	0.2806***	0.2767***	0.3037***
	(0.0314)	(0.0311)	(0.0287)
Constant	−0.1136***	−0.1244***	−0.1262***
	(0.0324)	(0.0378)	(0.0292)
Robust	Y	Y	N
Drop small	N	Y	N
Weights	N	N	Y
F	4.63	5.08	12.00
N	156	150	156

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each column reports the results from a separate regression, where the dependent variable is %$\Delta L_{e,r}$, the change in the size of an (e,r) cell, and the main explanatory variable is $Z_{e,r}/L_{e,r,2001}$, the "imputed" migrant inflow (defined in Section 3.2, Eq. (6)). All specifications include region and education fixed-effects. The weights used are $((L_{r,2001}^{(-1)})+(L_{r,2006}^{(-1)}))^{(-0.5)}$.

Equipped with our instrument, we can now estimate the causal labor market effects of immigration-induced changes in regional skill supplies. Our strategy provides identification of the effect of immigration shocks on wages and employment, as well as a test of the Rybczynski theorem. These are all the possible channels of adjustment within the context of the standard general equilibrium, open economy model.

4.3. Wage and employment results

Table 1 reports the average growth in employment rates and (nominal) wages for all education groups.[31] First, note that employment rates at all education levels increased approximately by 5 percentage points on average. Nominal wages also increased substantially over the period, with slightly higher average increases at low education levels. Specifically, nominal wage growth in the 2001–2006 period for high-school dropouts, high-school graduates, and college graduates was 29%, 27%, and 26%, respectively. These figures imply wage increases also in real terms for all three skill groups. Additionally, the lower wage growth at higher education levels suggests that cohort effects are the main shifter of the relative supply of skills in the average region.[32]

The top panels in Tables 4 and 5 report OLS estimates for the wage and employment regressions. We find small and non-significant effects of increases in the size of one skill group in a region on the wages of that same group (see the top panel of Table 4). The coefficient in our preferred specification (column 3) is in fact positive, although very small (0.0068). However, we suspect the OLS coefficients may be upwardly biased due to the endogeneity of migrants' location choices. The bottom panel in Table 4 reports the IV estimates for the wage regressions. The preferred specification shows small negative coefficients (lower than OLS) but still very small

[28] Ceuta and Melilla are two Spanish provinces located in the African continent.

[29] Note that the first-stage regression can be interpreted as a test of the hypothesis of perfect displacement of natives by immigrants. Since the estimated coefficient is significantly larger than zero, we reject perfect displacement. An "exogenous" inflow of foreign-born workers with a given skill level leads to an increase in the total population with that skill level, and the coefficient is close to one (in fact, we cannot reject it is equal to one).

[30] The instrument is also relevant and strong when we use the broader age-range of 25 to 54.

[31] The aggregate wage figures by education and region are constructed from individual-level median wage regressions, estimated separately for 2001 and 2006 and controlling for age, gender and migrant status. Using medians instead of means helps mitigate the problem of censoring in the wage data. See Appendix A for details.

[32] Table A1 reports nation-wide median wages by education for years 2001 and 2006. Despite the reduction in the COG–HSG and in the HSG–HSD wage ratios, returns to education are still substantial.

Table 4
Wage regressions.
Data sources: 2001 and 2006 LFS, 2006 CSWL, and 1991 Census.

Dependent variable: Change in log wage in a province-education cell, 2001–06 ($\Delta \ln w_{e,r}$)			
	1	2	3
OLS			
Population % change ($\%\Delta L_{e,r}$)	−0.0096	−0.0050	0.0068
	(0.0167)	(0.0200)	(0.0220)
High school grads.	−0.0257**	−0.0284**	−0.0388***
	(0.0102)	(0.0119)	(0.0108)
College grads.	−0.0309***	−0.0334***	−0.0468***
	(0.0096)	(0.0110)	(0.0095)
Constant	0.2943***	0.2968***	0.2988***
	(0.0063)	(0.0066)	(0.0049)
IV			
Population % change ($\%\Delta L_{e,r}$)	−0.0599	0.0331	−0.0095
	(0.0547)	(0.0684)	(0.0677)
Robust	Y	Y	N
Drop small	N	Y	N
Weights	N	N	Y
N	156	150	156

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each column reports the results from a separate regression, where the dependent variable is $\Delta \ln w_{e,r}$, the change in the log daily wage in an (e,r) cell, and the main explanatory variable is $\%\Delta L_{e,r}$, the percent change in the population of each cell. The wage figures are calculated for year-round, full-time workers, excluding self-employed (see Appendix A for details on the construction of the wage variable). All specifications include region and education fixed-effects. The weights used are $((L_{r,2001}^{(-1)})+(L_{r,2006}^{(-1)}))^{(-0.5)}$.

Table 5
Employment rate regressions.
Data sources: 2001 and 2006 LFS, and 1991 Census.

Dependent variable: Change in the employment rate, 2001–2006 ($\Delta NR_{e,r}$)			
	1	2	3
OLS			
Population % change ($\%\Delta L_{e,r}$)	0.0192	0.0296	0.0238
	(0.0216)	(0.0193)	(0.0196)
High school grads.	−0.0002	−0.0064	−0.0172
	(0.0103)	(0.0092)	(0.0096)
College grads.	−0.0039	−0.0068	−0.0106
	(0.0094)	(0.0091)	(0.0085)
Constant	0.0500***	0.0523***	0.0555***
	(0.0042)	(0.0042)	(0.0044)
IV			
Population % change ($\%\Delta L_{e,r}$)	0.0435	0.0884	0.0848
	(0.0476)	(0.0864)	(0.0630)
Robust	Y	Y	N
Drop small	N	Y	N
Weights	N	N	Y
N	156	150	156

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each column reports the results from a separate regression, where the dependent variable is $\Delta NR_{e,r}$, the change in the employment rate in an (e,r) cell, and the main explanatory variable is $\%\Delta L_{e,r}$, the percent change in the population of each cell. All specifications include region and education fixed-effects. The weights used are $((L_{r,2001}^{(-1)})+(L_{r,2006}^{(-1)}))^{(-0.5)}$.

and not significantly different from zero.[33] Even if we take at face value the largest negative coefficient (in column 1), we would conclude that a 10% increase in labor supply leads to a wage reduction of 0.6% in a given region and skill group, a very small effect.

Table 5 reports our estimates for the employment regressions.[34] The OLS specifications (see top panel) yield small, positive coefficients that are not significantly different from zero. The IV point estimates, shown in the bottom panel, are still positive, and larger than the OLS coefficients. This could reflect measurement error, but standard errors also increase proportionally and we cannot reject a zero value.[35] We thus conclude that migration inflows did not result in lower employment rates, since not only are the IV coefficients insignificant, but they in fact have a positive sign.[36]

Overall, our IV estimates suggest that an increase in the supply of a particular skill group in a region had no significant negative effect on the wages or employment rates of that group.

To check robustness we carry out an additional exercise. As noted earlier, annual salaries in the CSWL data are both top and bottom coded. The latter feature can be used to derive an additional test. If an increase in the size of a skill group leads to downward pressure on wages, we would expect an increase in the number of workers whose salary is bottom coded, particularly when we focus on relatively low-educated labor markets. Looking at the average for Spain as a whole, fewer people were bottom coded in 2006 than in 2001.

We are interested in whether high immigration regions experienced a relatively higher increase (or lower decrease) in the fraction of workers that are bottom coded. To test this hypothesis we run an additional regression where the dependent variable is given by the change in the fraction of the population in a province-education cell with bottom-coded salaries. On the right hand side of the regression, we have the usual education and province fixed effects, as well as the usual percentage change in the size of the province-education cell. Table 6 reports the results.

Table 6
Additional wage regressions.
Data sources: 2001 and 2006 LFS and 2006 CSWL.

Dependent variable: Change in the fraction of the province-education cell whose salary is bottom-coded, 2001–2006			
	1	2	3
OLS			
Population % change ($\%\Delta L_{e,r}$)	−0.0165	−0.0076	−0.0138
	(0.0156)	(0.0082)	(0.0096)
IV			
Population % change ($\%\Delta L_{e,r}$)	−0.0672	−0.0346	−0.0360
	(0.0791)	(0.0304)	(0.0303)
Robust?	Y	Y	N
Drop small?	N	Y	N
Weights?	N	N	Y
N	156	150	156

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each column reports the results from a separate regression, where the dependent variable is the change in the fraction of the province-education cell whose salary is bottom-coded, and the main explanatory variable is $\%\Delta L_{e,r}$, the percent change in the population of each cell. All specifications include region and education fixed-effects. The weights used are $((L_{r,2001}^{(-1)})+(L_{r,2006}^{(-1)}))^{(-0.5)}$.

[33] The results are analogous when we include all individuals 25 to 54. The OLS coefficients are very similar (small and insignificant), and the IV results are also close. In specification 3, the coefficient is 0.0089 (compared with the baseline −0.0095), again with a large standard error (0.06). Thus, these additional results support the interpretation of a zero effect on wages.

[34] Theoretically, an immigration shock has ambiguous effects on employment–population rates. On the one hand, an increase in the supply of a particular skill type may induce lower employment rates to the extent that it reduces wages and induces a reduction in labor market participation (Altonji and Card, 1991). On the other hand, it is well established that recent immigrants have lower reservation wages than native workers, which may lead to increases in the overall employment–population ratio.

[35] When we include individuals 25 to 54, the OLS coefficients are closer to zero and still insignificant. The IV results are also insignificant, and the magnitudes are similar. In specification 3, the coefficient is 0.078 (compared with the baseline 0.085).

[36] We also estimate regressions for the effect on the employment rate of natives only, with very similar results (see Table A2 in Appendix A). The preferred IV coefficient is 0.094 (not significant), thus we can also reject a negative effect on the employment rate of natives.

The OLS coefficient ranges from −0.0076 to −0.0165 across our specifications. This suggests that increases in the size of a skill group are *not* associated with increases in bottom-coding. However, the coefficients are very small and not significantly different from zero. We also conduct an IV estimation. The coefficient of interest remains negative and not significant. In conclusion, we cannot reject that immigration had no effect on the size of the population whose salaries are bottom-coded.

In summary, our results suggest that immigration had no significant effect on employment rates or wages in the period 2001–2006, despite significantly altering regional skill distributions. This finding is in line with the results in Lewis (2003) for U.S. metropolitan areas.[37]

As noted earlier, our analysis assumes perfect substitution between natives and immigrants with the same education levels. As a result, our estimates may be capturing an average of the combined effects of immigration on the labor market outcomes of natives and immigrants. To the extent that immigrants tend to have lower wages and employment rates than comparable natives, our estimates thus reinforce the conclusion that immigrants did not depress the wages or employment rates of native workers with the same education level.

4.4. Industry results

The results in the previous section show that immigration-driven increases in the size of a skill group in a region have no effect on the wages or employment rates of that group. This is at odds with the predictions of standard one-sector models. However, it may be the case that Rybczynski effects are at play. The goal of this section is to estimate the effects of the immigration shock on the structure of production of Spanish provinces and, in particular, provide a formal test of the Rybczynski theorem, which would be consistent with the earlier finding of wage insensitivity to labor inflows.

Table 1 contains the average values for the growth in each of the four components defined in Eq. (4). The average between-industry term, within-industry term, interaction term, and non-employment term are, respectively, 0.14, 0.02, 0.02, and −0.02. Thus, a priori, it would seem that the between-industry adjustment predicted by Rybczynski may be playing an important role.

4.4.1. Between-industry adjustment

First we estimate what fraction of an increase in the supply of a skill group is absorbed through increases in the employment of that factor owing to changes in industry mix, while keeping the skill intensities in all sectors constant at their pre-shock values. More specifically, we estimate Eq. (5) with dependent variable:

$$B_{e,r} = \sum_j \sigma^j_{e,r,0}\left(\%\Delta N^j_r\right),$$

where $B_{e,r}$, the between-adjustment term for skill e in region r, is a weighted sum of the percentage increase in the size of each industry (measured by total employment), and the weights capture each industry's relative size as an employer of each skill type in the region in the initial year. Intuitively, we expect that an increase in the size of a skill group will lead to an expansion of the sectors that use that skill intensively, followed by larger exports of these goods to other regions. Thus, a between-industry adjustment that operates through industries producing non-traded goods would not validate the Rybczynski prediction.

Table 7 presents the results. The OLS estimate in our preferred specification (column 3) is 0.14, quite precisely estimated. This point estimate implies that only about 14% of the absorption of a given skill inflow can be accounted for by changes in the structure of employment, keeping skill intensities unchanged. Due to the endogeneity problem, this coefficient cannot be given the causal interpretation of the response to an immigration shock. A plausible, alternative interpretation for this coefficient is the following. During the period of interest, regions experiencing a positive demand shock to an unskilled-labor-intensive sector may have attracted workers with those skills in larger numbers. In other words, the OLS coefficient is a convolution of labor demand and labor supply shocks. However, the Rybczynski theorem only refers to the latter type of shocks.

Turning to the IV estimates in Table 7, we can now interpret the coefficient as the size of the between-industry absorption in response to a labor supply shock. In our preferred specification (column 3), the point estimate is 0.07. The coefficient is smaller than before and not significantly different from zero.

It is possible that the previous results fail to uncover the between-industry adjustment because we are including non-traded as well as traded sectors in our analysis. Namely, in environments with non-traded goods, the Rybczynski theorem states that an exogenous increase in the supply of one factor will only leave factor prices unchanged if it is fully absorbed through a between-industry adjustment affecting only the industries producing traded sectors. Thus by restricting to traded sectors we expect the between-industry adjustment to become stronger, under the null of the Rybczynski hypothesis. The second panel in Table 7 presents the results for traded sectors only.[38] According to the Rybczynski theorem these should be the key sectors in absorbing labor inflows, and their increase in output would be exported to other provinces or to the rest of the world. The estimated coefficient falls to 0.04 and 0.02 in the OLS and IV estimation, respectively.[39]

Table 7
Output mix (between-industry) regressions.
Data sources: 2001 and 2006 LFS, and 1991 Census.

Dependent variable: Between-industries adjustment, 2001–2006 ($B_{e,r}$)	1	2	3
All sectors			
OLS			
Population % change ($\%\Delta L_{e,r}$)	0.1428***	0.1478***	0.1415***
	(0.0347)	(0.0410)	(0.0305)
IV			
Population % change ($\%\Delta L_{e,r}$)	−0.0183	0.2049	0.0668
	(0.1596)	(0.1349)	(0.0964)
Only traded sectors			
OLS			
Population % change ($\%\Delta L_{e,r}$)	0.0435***	0.0370*	0.0356**
	(0.0165)	(0.0193)	(0.0154)
IV			
Population % change ($\%\Delta L_{e,r}$)	0.0335	0.0511	0.0203
	(0.0355)	(0.0649)	(0.0474)
Robust	Y	Y	N
Drop small	N	Y	N
Weights	N	N	Y
N	156	150	156

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each column reports the results from a separate regression, where the dependent variable is $B_{e,r}$, the weighted % change in employment by industry in an (e,r) cell at the 2001 factor intensities, and the main explanatory variable is $\%\Delta L_{e,r}$, the percent change in the population of each cell. All specifications include region and education fixed-effects. A 30-industry classification is used. The weights used are $((L^{(-1)}_{r,2001}) + (L^{(-1)}_{r,2006}))^{(-0.5)}$.

[37] Lewis (2003) estimates a wage elasticity of 0.09, using instrumental variables.

[38] Here we use the classification for traded sectors used by Lewis (2003) and Hanson and Slaughter (2002). In the following section we estimate separate regressions for each industry.

[39] An alternative implementation of the between-industry regression can be done by using industry output as a measure of size, instead of industry employment. Unfortunately, the Spanish regional accounting data are released with substantial delay. The currently available data stops in year 2004. In his study with US data, Lewis (2003) shows that the two measures deliver very similar results.

Table 8
Worker mix (within-industry) regressions.
Data sources: 2001 and 2006 LFS, and 1991 Census.

Dependent variable: Within-industry adjustment, 2001–2006 ($W_{e,r}$)			
All sectors	1	2	3
OLS			
Population % change ($\%\Delta L_{e,r}$)	0.5502***	0.5548***	0.5392***
	(0.0367)	(0.0273)	(0.0267)
IV			
Population % change ($\%\Delta L_{e,r}$)	0.7481***	0.4518***	0.6035***
	(0.1990)	(0.1019)	(0.0844)
Robust	Y	Y	N
Drop small	N	Y	N
Weights	N	N	Y
N	156	150	156

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each column reports the results from a separate regression, where the dependent variable is $W_{e,r}$, the weighted % change in factor intensities by industry, and the main explanatory variable is $\%\Delta L_{e,r}$, the percent change in the population of each cell. All specifications include region and education fixed-effects. A 30-industry classification is used. The weights used are $((L_{r,2001}^{(-1)})+(L_{r,2006}^{(-1)}))^{(-0.5)}$.

4.4.2. Within-industry adjustment

Next we estimate the fraction of a given increase in the supply of a skill group that is absorbed through a more intensive use of that factor in the typical industry operating in the region, while keeping the regional economy's output mix constant at its initial 2001 values. That is, we estimate Eq. (5) using as dependent variable the within-industry adjustment:

$$W_{e,r} = \sum_j \sigma_{e,r,0}^j \left(\%\Delta\lambda_e^j\right),$$

which is a weighted sum across all industries in region r of the percentage change in the share of workers with skill type e employed in each industry. In one-sector models, an increase in the supply of unskilled labor will necessarily be absorbed through within-industry changes and will require a reduction in unskilled wages.

Table 8 displays the results. The OLS estimate in our preferred specification is 0.54, estimated with high precision. The IV estimate is even larger, 0.60 and also quite precisely estimated. These coefficients imply that about 60% of the absorption can be accounted for by increases in employment arising from a more intensive use of that factor. This result has important implications, which we discuss below.

4.4.3. Overall employment absorption

Finally, we provide estimates for the two remaining channels of absorption of labor inflows: increases in non-employment and increases in employment that involve simultaneous changes in regional output mix and industry skill intensities. Equipped with the whole set of estimates, we shall then provide a test of the ability of standard open economy models to account for the economic effects of immigration.

Let us begin by estimating what fraction of a given skill inflow is absorbed by increases in unemployment or non-participation. Table 9 (last column) presents the summary of our estimates. The OLS estimate in our preferred specification is 0.17, estimated quite precisely. The IV point estimate is 0.11, but the increase in the standard error makes this value not statistically different from zero. Taken together, these estimates suggest that a small fraction of the inflows were absorbed through increases in non-employment. Note that this is not inconsistent with our earlier finding that immigration did not lead to lower overall employment rates. The reason is that the employment rates of natives and immigrants were very similar in this period. As a result, the increased number of non-employed individuals in the economy did not affect the total employment–population rate.[40]

Table 9
Summary of absorption channels.
Data sources: 2001 and 2006 LFS, and 1991 Census.

Dep. var.	Between	Within	Interaction	Non-employment
OLS				
Population % change	0.1415***	0.5392***	0.1491***	0.1702***
($\%\Delta L_{e,r}$)	(0.0305)	(0.0267)	(0.0230)	(0.0224)
IV				
Population % change	0.0668	0.6035***	0.2244***	0.1052
($\%\Delta L_{e,r}$)	(0.0964)	(0.0844)	(0.0742)	(0.0715)

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each column reports the results from a separate regression, where the main explanatory variable is $\%\Delta L_{e,r}$, the percent change in the population of each cell. See Eq. (4) for the definition of the 4 absorption channels (dependent variables). A 30-industry classification is used. All specifications include education dummies and region fixed effects, and use weights $((L_{r,2001}^{(-1)})+(L_{r,2006}^{(-1)}))^{(-0.5)}$.

As shown in Eq. (4), there is a fourth term in the decomposition, an interaction between changes in skill intensity and output mix. As shown in Table 9, the point estimate in this regression ranges from 0.15 (OLS) to 0.22 (IV). In both cases, we reject values of zero.

We can now summarize the pattern of absorption implied by our IV estimates. Consider an exogenous inflow of unskilled workers into a region. Except for 11% of the inflow, the remaining 89% would be absorbed through increases in the number of (unskilled) employed individuals. The increased employment is accounted for by within-industry absorption (60%), absorption involving both changes in the output mix and in the worker mix (22%), and between-industry absorption (7%).[41] Clearly, the lion's share of the inflow of unskilled workers into a region is absorbed through an increase in the intensity of use of unskilled labor in the typical industry in the region, relative to the global changes in skill intensities in the country as a whole.[42]

These results have important implications. The prominent role of the within-industry adjustment together with the insensitivity of wages to changes in the relative supply of skilled labor *cannot* be accounted for by standard open economy models. In these models, firms vary their optimal skill intensity only if relative wages induce them to do so.[43]

Overall, our results confirm the puzzle that has also been documented for other countries. Lewis (2003) and Dustmann and Glitz (2008) find that local and regional economies in the U.S. and Germany, respectively, adjust to immigration flows in a very similar way as Spanish regions do.

4.4.4. Results by industry

In order to understand better the specifics of the Spanish experience, we finally turn to a more detailed study of the role played by individual sectors in the absorption of recent immigration flows.

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[40] Or the employment rate of natives (see footnote 36 and Table A2 in Appendix A).

[41] The main pattern is still present when we extend the data set to include ages 25 to 54: we still find small, insignificant between-industry adjustment and large, significant within-industry effects. The OLS coefficients are very similar in both magnitude and precision. In IV, the between effect is still insignificant, increasing from 0.067 to 0.11. The within effect falls from 0.60 to 0.54 and it remains strongly significant, while the unemployment effect increases from 0.105 to 0.138 and it becomes significant.

[42] We also estimated the models using a coarser 16-industry classification. The results were qualitatively similar, with between-industry absorption playing a very minor role. This suggests that the role of between-industry absorption is not increasing as the number of industries rises. In a contemporaneous study by Dustmann and Glitz (2008) using German firm-level data between-industry absorption does not play a significant role either.

[43] We note that we consider a relatively short time period (5 years). Thus, it is realistic to assume that there were no region-specific technological changes that affected relative factor demands.

Table 10
Contribution to between and within absorption by industry.
Data sources: 2001 and 2006 LFS, and 1991 Census.

Dep. var.		Between	Within
	All industries	0.0383	0.5884***
1	Agriculture	0.0171	0.0343
2	Fishing	0.0087**	0.0220*
3	Mining	−0.0029	−0.0036
4	Manufactures	−0.0308*	0.0244
5	Utilities	−0.0039	−0.0023
6	Construction	−0.0011	0.0662*
7	Retail	0.0025	0.1242***
8	Hotels and rest.	−0.0045	0.0802**
9	Transport	0.0190*	0.0232
10	Finance	−0.0069	0.0304
11	Real estate	0.0022	0.0281
12	Public adm.	0.0883**	0.1140**
13	Education	−0.0297	0.0252
14	Health	−0.0214	−0.0025
15	Other social serv.	0.0262**	−0.0115
16	Domestic service	−0.0244	0.0362**

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: Each column reports the results from a separate IV regression, where the main explanatory variable is $\%\Delta L_{e,r}$, the percent change in the population of each (education, region) cell. A 16-industry classification is used. All specifications include education dummies and region fixed effects, and use weights $((L_{r,2001}^{(-1)}) + (L_{r,2006}^{(-1)}))^{(-0.5)}$.

Let us start with the between-industry adjustment. Recall from Eq. (4) that the between-industry adjustment corresponds to a weighted average of growth rates across all industries, measured by increases in total industry employment. We are now interested in the fraction of the change in the supply of a given skill group absorbed by each industry j. More specifically, we regress the between-industry term for each industry, B_e^j, on changes in the supply for that skill group. Table 10 reports the results.[44] With the exception of the fishing industry, which is practically negligible in terms of employment for all provinces, no other industry with tradable output played any significant role in the absorption of inflows. Interestingly, we find a significant and quantitatively non-negligible effect of increases in the size of a skill group on the (weighted) size of employment in public administration and in other social services. While this has nothing to do with Rybczynski effects, it is quite intuitive. Regions that experienced important increases in population had to expand the size of their public services.

Let us now turn to the role played by each industry in the within-industry adjustment. The dependent variable in our regressions is now the industry-weighted percentage change in the fraction of employment of a given skill type over total industry employment. The second column in Table 10 reports the results of regressing W_e^j on $\%\Delta L_{e,r}$, including education and region fixed effects. As we saw earlier, the within-industry adjustment accounts for roughly 60% of a given skill inflow. About half of the absorption is due to changes in skill intensities in retail, hotels and restaurants, construction, and domestic services, with public administration also playing an important role. To the extent that immigration flows have been mostly unskilled, these industries have increased their intensity of use of unskilled labor in high-immigration regions, relative to the changes in skill intensity in other provinces.

Our interpretation for why these particular industries have played a larger role is that they may be characterized by technologies that allow for a larger substitution across education groups, as well as being large in terms of employment. We also note that the industries that have absorbed most of the new labor inflows produce non-traded goods.

[44] The main analysis (Tables 7–9) is performed based on a 30-industry classification. This section reports the results using a coarser 16-industry classification for the sake of clarity.

5. Conclusions

We study the effects of recent migration flows on Spanish regional labor markets. The Spanish case is particularly suitable for this type of analysis given the large magnitude of the inflows in a very short time frame and from very low initial levels. Moreover, the inflows affected some regions much more than others, providing large cross-sectional variation. In terms of identification, we take advantage of the fact that immigrants' location choices were strongly driven by earlier migrant settlements for some of the main countries of origin.

We find that the relatively unskilled migration inflows did not affect the wages or employment rates of unskilled workers in the receiving regions. Our finding that immigration did not seem to affect wages in Spain confirms the findings in Carrasco et al (2008) for a more recent period. This is reassuring, given the differences in the data and methodology between the two studies.[45]

Our results suggest that the increase in the unskilled labor force was absorbed mostly through increases in total employment. This increase did not originate from changes in output mix, but was instead driven by changes in skill intensities. The average industry responded to the increase in the supply of unskilled workers by using the more abundant type of labor more intensively. In particular, the industries that played the main role were retail, construction, hotels and restaurants and domestic services, as well as the public sector. All these industries produce non-traded goods. Overall, the response of Spanish regions to immigration shocks is remarkably similar to the response found by Lewis (2003) and Dustmann and Glitz (2008) for the US and Germany, respectively. By implication, the large differences in labor market institutions among these three countries do not appear to shape the channels through which local economies absorb immigration flows. Moreover, the pattern of adjustment documented in these studies is inconsistent with standard open economy models: the labor supply shocks induced by immigration substantially alter the skill composition of employment at the industry level without having an effect on the wage structure or on the regional industry composition. Hence, a new theory of local and regional economies is needed that can account for this robust set of facts.

Currently, immigration economists are busy searching for such a theory. A promising venue builds on the idea that immigration shocks induce changes in production technologies at the industry level.[46] Another potential explanation is that natives and immigrants are imperfect substitutes in production even controlling by education (Peri and Sparber, 2009). In fact, our finding that immigration did not depress wages and employment rates in Spain is consistent with the results in Amuedo-Dorantes and De la Rica (2008), who show that Spain-born workers have shifted toward occupations less exposed to immigration (more communication-intensive).[47]

In our view, future work should also focus on the role of physical capital. At the local or regional level capital flows face no impediments and thus are potentially very large. If the degree of substitution between capital and the different skill groups differ, it may be possible to build an alternative explanation for the evidence found in this paper. More broadly, it will be interesting to follow the assimilation experience of Spain's recent

[45] In some specifications Carrasco et al. (2008) find small negative wage effects. Our estimates seem more robust, which may reflect the fact that our sample contains a larger number of immigrants and we use more comprehensive wage data based on social security records.

[46] See Lewis (2005) for some supportive evidence for the case of the US.

[47] Ortega and Polavieja (2009) provide new measures of labor market exposure to immigration and show that these significantly affect natives' attitudes toward immigrants.

immigrants as well as the potential consequences for Spain's domestic policy.[48]

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Appendix A

A.1. Data quality issues

There are reasons to believe that, relative to the US and some other countries, the Spanish LFS more accurately captures the demographics of the foreign-born population at the regional level, including the undocumented population. The reason is that Spain keeps a continuously updated Population Registry at the local level, which plays an important role in the sampling design of the LFS. All residents in Spain, regardless of their legal status, are required to register and simultaneously have a strong incentive to do so for a number of reasons. First, registration provides access to free public healthcare and schooling. Second, it is the main official proof of residence in the country, one of the main requirements to apply for legalization. Finally, the government does not use the information on the Registry to pursue potentially undocumented workers. For all these reasons, the data on the size and demographic characteristics of the foreign-born population in Spain is reasonably accurate and up-to-date.

A.1.1. Aggregation to province-education cells

The main analysis uses individual-level data aggregated to province-education-year cells. The size of each cell in the Labor Force Survey ranges from 122 to 5147 observations. Only 3 cells out of the total of 312 have less than 200 individual observations, and only 47 (15%) have less than 500. When we aggregate, we use the weights provided by the LFS that are derived from local registry data and are supposed to adjust the data for representativity at the regional level. For our estimates of migration inflows, we actually compared our LFS estimates with local registry data and found them to be very close. Although migration densities by region estimated with LFS data had somewhat lower levels than local registry data, the correlation between the two data sources was extremely high. We thus feel that LFS data are reasonably reliable for our purposes.

A.2. Definition of education groups

A.2.1. Labor Force Survey

The lowest education level (HSD) includes all individuals that are illiterate, or at most completed the first stage of secondary education, or that at most completed vocational training that only required the first stage of secondary education as a prerequisite. The intermediate education group (HSG) includes individuals that obtained a high-school degree ("bachillerato"), and individuals with middle-level and advanced-level professional training (which requires having completed secondary education). The highest education group (COG) includes individuals with a university degree or beyond.[49]

A.2.2. Continuous Sample of Working Lives

The CSWL contains information on educational attainment, obtained from local registry data ("Padrón Continuo"). If we define education groups using only this variable, the share of college graduates that results is far lower than in the LFS. For year 2006, and restricting to full-time, not self-employed, individuals with ages 25–45, the share of college graduates in the LFS is 27% while it is only 8% in the CSWL. This underestimate of the level of schooling in the CSWL can be traced to the local registry not updating the education information for native individuals that never change their municipality of residence. Fortunately, we can address this problem with the employer-reported information about the category of each employee. These categories refer to the skills required to perform a particular job. Specifically, we re-define education groups as follows. We assign an individual to the lowest education level if he is a HSD, under the definition above, *and* his current job is in the low-skill job categories.[50] An individual is assigned to the top education level if he is classified as a COG under the previous definition *or* his current job is in the high-skill job category (engineers, university graduates, firm managers).[51] All remaining individuals are assigned to the intermediate education category.[52] Under this new definition (the one that we use in the analysis), the fraction of college graduates in the population for year 2006 is 23%, only 4 percentage points lower than in the LFS.[53]

A.3. Construction of the aggregate wage variable

In order to construct our dependent variable measuring the percent change in wages in a given education-region cell, we proceed in two steps. First, we run log wage regressions at the individual level, separately for 2001 and 2006. We estimate median regressions in order to address the issue of top and bottom coding. As controls, we include age dummies, gender and migrant status, as well as interacted province and education dummies. Some descriptive statistics can be found in Table A1. From these dummies we then construct "predicted" median wages by region and education levels in both years, and by differencing we obtain the change in log wages between 2001 and 2006. The results of the individual-level wage regressions are available from the authors upon request.

Table A1
Median wages by education.
Data source: 2006 CSWL.

	2001	2006	% change (nominal)	% change (real)
ALL	41.5	54.0	30%	11%
HS dropouts	32.3	42.2	31%	11%
HS grads	45.2	55.3	22%	4%
College grads	68.2	81.5	19%	2%
N	159,723	143,568		

Note: Daily wage for full-time, year-round workers, by education (in Euros).

[48] Ortega (2005, 2010) analyzes the effects of immigration on the future evolution of immigration policy and the size of the welfare state.

[49] Specifically, HSD are individuals with values for "nforma" equal to 11, 12, 21, 22, 23, 31, 36, and 80. HSG are those with values equal to 32, 33, 34, 41, 51, 53. Finally, COG are individuals with values "nforma" equal to 52, 54, 55, 56, 61.

[50] The low-skill job category contains "grupos de cotización" 6 to 10.

[51] The high skill job category contains "grupos de cotización" 1 and 2.

[52] The intermediate education category thus includes "grupos de cotización" 3 to 5, plus those in groups 6 to 10 reporting HSG.

[53] Unfortunately, we know of no dataset containing both information on job categories and high-quality education levels, which would be useful in assessing the quality of our categorization.

Table A2

Employment rate regressions, only natives.
Data sources: 2001 and 2006 LFS, and 1991 Census.

Dependent variable: Change in the employment rate of *natives*, 2001–2006 ($\Delta NR_{e,r}$).			
	1	2	3
OLS			
Population % change	0.0199	0.0349*	0.0192
($\%\Delta L_{e,r}$)	(0.030)	(0.019)	(0.020)
IV			
Population % change	0.1161	0.0466	0.094
($\%\Delta L_{e,r}$)	(0.105)	(0.086)	(0.065)
Robust	Y	Y	N
Drop small	N	Y	N
Weights	N	N	Y
N	156	150	156

(* Significant at 10%; ** Significant at 5%; *** Significant at 1%).
Note: There are 52 provinces (subscripted r) and 3 education levels (subscripted e). Each column reports the results from a separate regression, where the dependent variable is the change in the employment rate of *natives* in an (e,r) cell, and the main explanatory variable is $\%\Delta L_{e,r}$, the percent change in the population of each cell. All specifications include region and education fixed-effects. The weights used are $((L_{r,2001}^{(-1)})+(L_{r,2006}^{(-1)}))^{(-0.5)}$.

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