How Do Very Open Economies Adjust to Large Immigration Flows? Recent 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 heterogeneity in immigration flows across the different regions. To identify causal effects, 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. The increase in the unskilled labor force was absorbed mostly through increases in total employment. This increase did not originate in changes in the output mix, but was instead driven by changes in skill intensity. In regions of high immigration, all industries increased the intensity of use of the now more abundant type of labor. 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.

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

In recent years Spain has received a massive wave of immigration, with the foreign-born share jumping from 6% in 2001 to 13% in 2006.[1] This paper studies how Spanish regional economies have 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 cross-country 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.

The long history of immigration in the U.S. has given rise to a vast literature on the economics of immigration.[3] 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.[4]

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[1] Local registry data at January 1st of each year. Population age 15-64.
[2] Chiswick and Hatton (2003).
[3] Important early contributions are Card (1990) and Borjas, Freeman and Katz (1996). Some recent important contributions include Borjas (2003), Ottaviano and Peri (2006), and Lewis (2003) among many others.
[4] A few influential studies are Hunt (1992) for France, Pischke and Velling (1997) for Germany, and Dustmann et al (2005) and Manacorda et al (2007) for the UK, and Carrasco, Jimeno and Ortega (2007) for Spain.

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 January 2001 and January 2006 (see Figure 1). During the same period, the foreign-born population in the U.S. went from 11 to 12.1%.[5]

Secondly, Spain is a new country of immigration and it is conceivable that the effects of immigration depend on the recent migration history of the country. Another feature of the Spanish experience is that a large fraction of recent immigrants are native Spanish speakers from Latin America. These special features together with the large size of the inflows make the Spanish experience highly interesting. Some researchers have already recognized this.[6]

Following the recent literature, we conduct a spatial correlations analysis focusing on regional economies.[7] 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.

[5] U.S. Current Population Survey.

[6] See, for instance, Carrasco, Jimeno, and Ortega (2007) and Amuedo-Dorantes and De la Rica (2007, 2008).

[7] The spatial correlations approach was pioneered by Altonji and Card (1991), and has been widely used since then. For some influential recent applications see Ottaviano and Peri (2006), Dustmann and Glitz (2007) and Saiz (2007).

Our methodology seems well suited to the Spanish case. First, there is very large regional variation regarding the size of immigration flows. Figure 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 usually 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 have 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.

Let us now turn to our main results. 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.[8]

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.[9] 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

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[8] See the surveys in Borjas (1994), Friedberg and Hunt (1995) and Card (2005).
[9] Rybczynski (1955).

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 exploration of this result is Hanson and Slaughter (2002), and Gandal, Hanson and Slaughter (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.

Our second result is that immigration did not significantly change regional output mix (between-industry absorption). In contrast, we show that the main channel of absorption of immigration-driven increases in the supply of a particular skill 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 pattern 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, which covers the whole period of interest, 2001-2006. In addition, we are the first to show that the Card-type instrument is useful also for Spain to identify the causal labor market effects of immigration.[10]

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 setup

Our setup is a version of the small-open economy model that is very often used in the labor and empirical trade literature.[11] We view each province as a small open economy.[12] There are J final goods (sectors), produced using three types of labor, differentiated by skill levels (defined by education). Within education groups, natives and immigrants are considered perfect substitutes. 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.[13]

[10] Blanes et al (2008) also analyze the effects of immigration on the structure of production 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).
[11] Leamer (1995), Hanson and Slaugher (2002) and Gandal, Hanson and Slaughter (2005).
[12] Note that we use the terms "province" and "region" interchangeably throughout the paper.
[13] Implicitly, we are assuming that natives and immigrants with the same education level are perfect substitutes. This assumption has recently been challenged by Ottaviano and Peri (2004) and Peri and Sparber (2008). However, Borjas, Grogger and Hanson (2008) maintain that there is no convincing

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:[14]

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

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 useless for production, and are not employable by any sector. 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 population of an education group can be decomposed into the (weighted) sum of the percentage increases in the employed and the non-employed population:

evidence so far to reject the assumption of perfect substitution. In addition, a large fraction of immigrants in Spain are native Spanish speakers or their mother tongues are relatively close to Spanish. This is likely to increase their degree of substitution with native workers with the same education levels.

[14] Alternatively, we can interpret that goods are 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.

$$\frac{\Delta L_e}{L_{e,0}} = \%\Delta L_e = \frac{N_{e,0}}{L_{e,0}}\left[\%\Delta N_e\right] + \frac{U_{e,0}}{L_{e,0}}\left[\%\Delta U_e\right]. \quad (3)$$

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, 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: *($\%\Delta L_1$, $\%\Delta L_2$, $\%\Delta L_3$)*. Some algebra delivers the following accounting identity. For each education group e=1,2,3, the increase in the economy-wide employment for that group can be decomposed in non-employment (UE), a purely between-industry adjustment (B), a purely within-industry adjustment (W), and an interaction term (I). Formally,

$$\begin{aligned}\%\Delta \mathrm{L}_\mathrm{e} &= \mathrm{UE}_\mathrm{e} + [\mathrm{B}_\mathrm{e} + \mathrm{W}_\mathrm{e} + \mathrm{I}_\mathrm{e}] \\ &= (1-\sigma_{\mathrm{e},0})[\%\Delta \mathrm{U}_\mathrm{e}] + \sum_\mathrm{j} \sigma^{j}{}_{\mathrm{e},0}[\%\Delta \mathrm{N}^\mathrm{j}] + \sum_\mathrm{j} \sigma^{j}{}_{\mathrm{e},0}[\%\Delta \lambda^{j}{}_\mathrm{e}] + \sum_\mathrm{j} \sigma^{j}{}_{\mathrm{e},0}[\%\Delta N^{j}][\%\Delta \lambda^{j}{}_\mathrm{e}]\end{aligned} \quad (4)$$

where $\sigma^{j}_{e,0}$ 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:

$$\sigma^{j}{}_{e,0} = \frac{N^{j}{}_{e,0}}{L_{e,0}}, \qquad \lambda^{j}{}_{e} = \frac{N^{j}{}_{e}}{N^{j}}, \qquad \sigma_{e,0} = \sum_{j} \sigma^{j}{}_{e,0}.$$

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 sectoral 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.[15]

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 sample of Social Security records. We also make use of the 1991 Census to build our instrument. Let us describe each of these in more detail.

We use the four quarters of the 2001 and 2006 LFS. We obtain detailed individual-level information on province of residence, educational attainment, age, country of birth, and employment by industry. Throughout the paper, we define immigrants as foreign-

[15] 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.

born workers. The LFS also reports years since arrival for each foreign-born worker. We define three education levels: high-school dropouts (HSD), high-school graduates (HSG), and individuals with completed university studies (COG). The interested reader can refer to the appendix for further details on the exact definition of education groups. All variables in the analysis except wages and (partially) the instrument are constructed from LFS data.

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 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,[16] his full-time or part-time status, and whether he is self-employed. We will mainly focus on daily wages (as in Lacuesta et al., 2008) for full-time, year-round workers, excluding the self-employed.

There are two important limitations of this data set. The first is that annual salaries are severely bottom and top coded. 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

[16] In Spanish, worker category corresponds to "Grupo de cotización".

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 more details in the data appendix.

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.

We restrict the analysis to population in the age group 25-45. We discard very young individuals to obtain reasonable estimates of the fraction of the population with university education, and we discard individuals approaching retirement to reduce the number of inter-regional migrants driven by retirement motives. This age group contains the bulk of the working-age, foreign-born inflows during the period we consider.

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.

3.2. Empirical Strategy

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

$$Y_{e,r} = \beta \frac{\Delta L_{e,r}}{L_{e,r}^{2001}} + \alpha_e + \mu_r + \varepsilon_{e,r}. \tag{5}$$

We start by using wages and employment rates as our dependent variables, and later move on to estimating between and within industry absorption. In all cases, the main regressor is the percentage increase in the size of the population of a region-education cell. We allow slope coefficient β to vary across models, however we impose symmetric values across regions and education levels.[17]

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.[18]

We first estimate the effect of the immigration shock 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 ($\Delta lnw_{e,r}$). It may be the case that we find that 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 now a wide consensus that immigration has at most a very small impact on the regional wage structure.

[17] This is the case when sector-specific production functions are CES.
[18] We weigh each cell by $((L_{r,2001}^{(-1)}) + (L_{r,2006}^{(-1)}))^{(-0.5)}$, as in Lewis (2003).

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 skill groups in the different regions have been absorbed by a) increases in non-employment (UE), b) between-industry changes in employment (B), c) within-industry changes in employment (W), and d) an interaction of the latter two channels (I), as defined in equation 4. According to the Rybczynski theorem, we should find that

$$\beta_B + \beta_{UE} = 1$$
$$\beta_W = \beta_I = 0,$$

where these coefficients are obtained from estimating the respective regression.

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' 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).[19] 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 in a robust feature of

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

immigration flows, the existence of migration networks. Immigrants tend to locate in regions (or even neighborhoods) 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 $M_{e,c}^{Sp}(2001-2006)$ 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. During that period, the Spanish economy was characterized by staggeringly high unemployment rates, suggesting that these arrivals were mainly driven by "push factors".

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:

$$Z_{e,r} = \sum_{c=1}^{C} Z_{e,r,c} = \sum_{c=1}^{C} \pi_{r,c}(1991) M_{e,c}^{Sp}(2001-2006) \tag{6}$$

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 25-45-year-old population grew by 10%, with 90% of the growth being attributable to inflows of foreign-born (Registry Data 2001 and 2006).

Table 1 shows that the average increase in the size of education-province cells was almost 16%, ranging from a sharp drop of 36% to a spectacular increase of 107%. 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 per cent of the initial cell size, and up to 59 percent.

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 have been relatively unskilled. While on average the 2001-2006 inflows of foreign-born workers have increased the size of the COG population by 7%, they have 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.[20]

Another salient feature of the recent Spanish immigration experience is its highly unequal regional impact. Figure 2 reports the foreign-born share for the 52 Spanish provinces in 2006. For the provinces lying on the Mediterranean or around Madrid, over 20% of the population in the 25-45 age group was foreign-born. In contrast, in most of the South and West of the country the share of foreign-born in the population in 2006 remained below 5%.

Even more relevant for our purposes, the skill composition of the inflows of foreign-born workers also varied across regions. Figure 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 degree line. That is, the fraction of college graduates among the foreign-born population in most regions is lower than for natives. It turns out that the provinces that received large inflows are also those for which immigrants were relatively 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%.

[20] In the LFS we can disaggregate education levels further. In particular, we can subdivide the HSD group between those with a primary education degree and those without. The group of primary-school dropouts increased by 14% of its initial size as a result of recent immigration flows with an overall reduction of 30%. In other words, the 2001-2006 immigration wave as a whole was even more unskilled, relative to natives, than the figures in table 1 suggest.

4.2. First Stage Results

As mentioned, OLS estimates of our coefficients of interest may be biased due to an endogeneity problem. Natives and immigrants with a given education level may be attracted to regions with a growing relative demand for their skills. In this case, OLS estimates would be biased.

To deal with this problem we build the instrument described in section 3.2. By construction, the inflows of foreign-born workers with a given education level imputed into a particular region are unrelated to current unobserved shocks to local labor markets.

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. 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 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.[21] Finally, column 3 uses weights and constitutes our preferred specification.[22] The use of efficient weights corrects for the potential heteroskedasticity, and this specification also facilitates the comparison of the results with those in Lewis (2003).

Across all specifications, the coefficient is highly significant and close to one, and the F-statistic ranges between 56 and 71. Thus, we conclude that the instrument is valid for the case of Spain, a country with a relatively recent immigration history.[23]

Equipped with our instrument, we can now attempt to 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

[21] Ceuta and Melilla are two Spanish provinces located in the African continent.
[22] We use weights $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$, as in Lewis (2003).
[23] We find no evidence of displacement of natives. See Card and DiNardo (2000).

well as a test of the Rybczynski theorem. These are all 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.[24] First, note that employment rates at all education levels increased approximately by 5 percentage points on average. Nominal (and real) wages also increased substantially over the period, with 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.[25]

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 wages and employment rates of that same group. However, we suspect these coefficients may be upwardly biased due to the endogeneity of migrants' location choices.

Our IV estimates suggest that an increase in the supply of a particular skill group in a region has no significant effect on the wages or employment rates of that group. The

[24] 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 the data appendix for details.

[25] 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.

bottom panel in table 4 reports the estimates for the wage regressions. The preferred specification (column 3) shows small negative coefficients (lower than OLS) but still not significantly different from zero.

Table 5 reports our estimates for the employment regression. The IV point estimates are positive, and larger than the OLS coefficients. However, standard errors also increase proportionally and we cannot reject a zero value.

In order to confirm the insensitivity of the wage distribution to immigration-driven labor supply shocks, we carry out an additional exercise. As noted earlier, annual salaries in the CSWL data are both top and bottom coded.[26] The latter feature can be used to derive an additional. 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 people 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 a 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 A2 reports the results.

[26] The nature of bottom coding in our data is the following. All employers are required a fraction of their workers' annual salary as Social Security contributions. Below 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 data does nor report the actual salary, but the fictional fixed salary that is used to compute the minimum contribution.

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 sum, our results suggest that immigration shocks have had no significant effect on employment rates or wage rates in the period 2001-2006, despite significantly altering regional skill distributions. This finding confirms the results in Lewis (2003) for U.S. metropolitan areas.[27]

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 equation 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.

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

Thus, a priori, the between-industry adjustment predicted by Rybczynski may be playing an important role.

Between-industry adjustment

First we estimate what fraction of a given increase in the supply of a skill group is absorbed through increases in the employment of that factor owing to changes in output mix, while keeping the skill intensities in all sectors constant at their pre-shock values. Intuitively, we expect an expansion of the sectors that use intensively the skills in larger supply, 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.[28]

Table 6 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.

[28] Output data could also be used to measure changes in the scale of each industry. However, data is currently available only up to 2004.

Turning to the IV estimates in table 6, 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.

The second panel in table 6 presents the results when we restrict to sectors with tradable output. [29] 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.

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, while keeping the regional economy's output mix constant at its 2001 values.

Table 7 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 of a given skill inflow 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.

[29] 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.

Overall employment absorption

Finally, we provide estimates for the two remaining channels of absorption of skill 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 in non-participation. Table 8 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 only a small fraction of the inflows were absorbed through increases in non-employment. As shown in equation 4, there is a fourth term in the decomposition, an interaction between changes in skill intensity and output mix. As shown in table 8, the point estimate in this regression ranges from 0.15 (OLS) to 0.22 (IV). In both cases, we reject values of zero.

Let us next 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 would be accounted for by within-industry absorption (60%), absorption involving both changes in the output mix and in the worker mix (22%), and by between-industry absorption (7%). Clearly, the lion's share of the inflow of unskilled workers into a region would be absorbed through a generalized increase in the intensity of use of unskilled labor in the typical industry in that region, relative to the global changes in skill intensities in the country as a whole.

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.

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.

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 industries in the absorption of recent immigration flows.

Let us start with the between-industry adjustment. Recall from equation 4 that the between-industry adjustment corresponds to a weighted average of growth rates for all industries, measured by increases in total industry employment:

$$\mathrm{B_e} = \sum_{\mathrm{j}} B_e^j = \sum_{\mathrm{j}} \sigma^j{}_{\mathrm{e},0}[\%\Delta \mathrm{N}^{\mathrm{j}}].$$

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 9 reports the results.[30] 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:

$$W_e^j = \sigma_{e,0}^j \left[\%\Delta\lambda_e^j\right]$$

where λ_e^j is defined as the ratio of workers with education "e" to all workers, in industry "j". The second column in table 9 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% 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 playing also 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 suffered by other provinces.

[30] The main analysis is performed with a 30-industry level of disaggregation. This section reports the results using a 16-industry classification for the sake of clarity.

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.

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, first, 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. 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. Most industries 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.

Our results strengthen the view that local and regional economies in Europe and in the US adjust similarly to immigration shocks, despite vastly different labor market institutions. And that this adjustment appears to be inconsistent with standard open economy models. Hence, a new theory is needed to account for this new 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.[31] While promising, there is still a great deal of work to be done in demonstrating that this mechanism can account for the documented empirical patterns. Additionally, a satisfactory explanation should be consistent with the recent findings regarding the imperfect substitution between natives and immigrants with similar education levels (Peri and Sparber, 2007).

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. We view the Spanish experience in the period we study here as a potentially interesting episode to examine this hypothesis.

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

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Figure 1. Share of the foreign-born population (age 25-44) in Spain.
Source: Registry data at January 1st of each year ("Padrón").

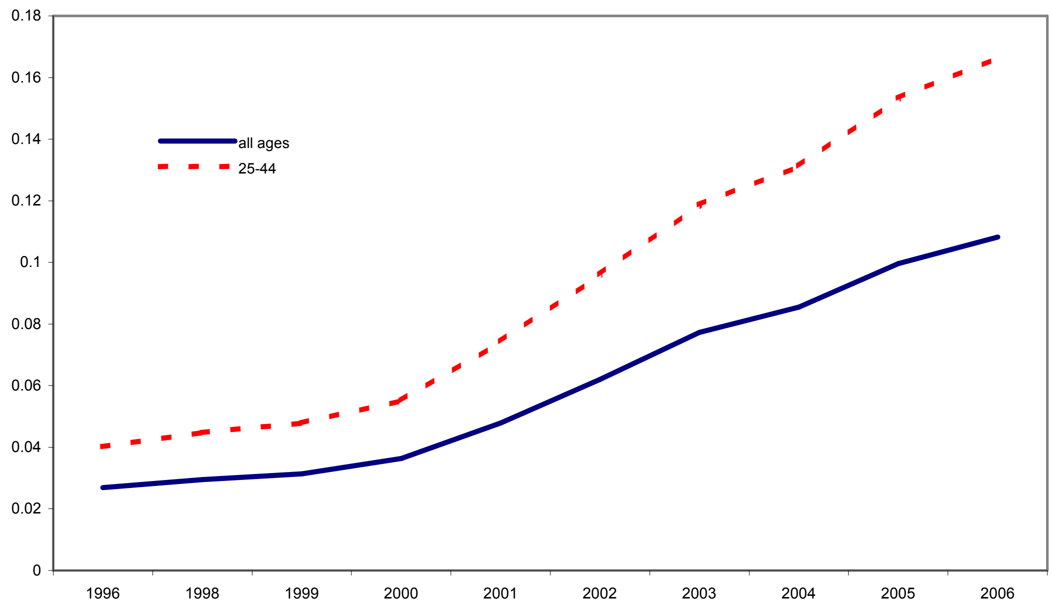

Figure 2. Foreign-born share in 2006 (age bracket 25-45) in Spanish provinces.
Source: 2006 Spanish Labor Force Survey (EPA).

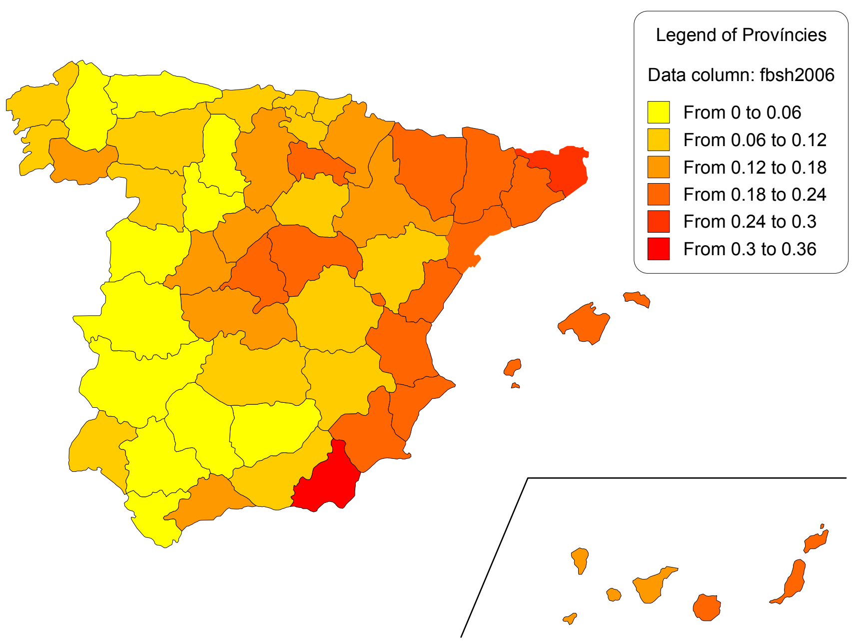

Figure 3: Fraction of college graduates among native and foreign-born population, year 2006.
Source: 2006 LFS, second quarter. Removed one outlier and two missing values.

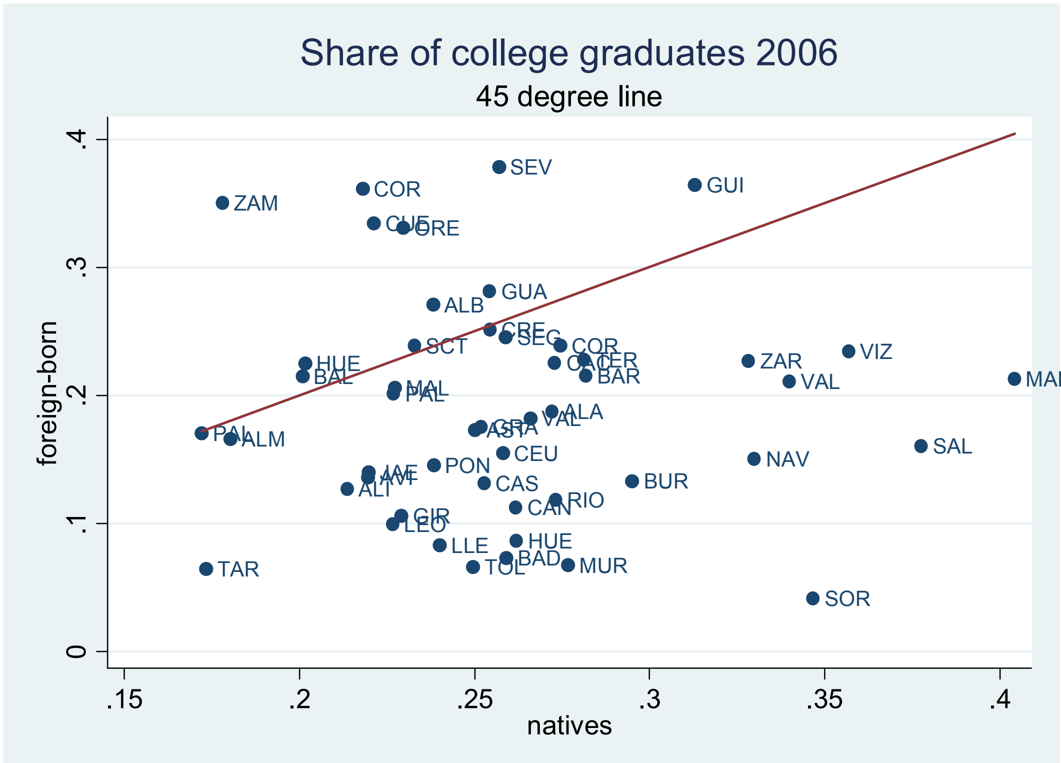

Table 1. Descriptive Statistics, 2001-2006

ALL

Variable	Obs	Mean	Std. Dev.	Min	Max
Population % change (%∆Ler)	156	0.1572	0.2404	-0.3640	1.0743
Migration inflow (Mer/Ler,2001)	156	0.0942	0.0918	0	0.5947
Imputed inflow (Zer/Ler,2001)	156	0.0986	0.1155	0.0081	1.0165
Percent change in emp. (%∆Ner)	156	0.2435	0.2662	-0.3015	12,672
Change in emp. rate (∆NRer)	156	0.0517	0.0381	-0.0706	0.1600
Percent change in wages (∆ln wer)	156	0.2739	0.0438	0.1946	0.4682
Between-industry absorption (Ber)	156	0.1414	0.1030	-0.1158	0.4468
Within-industry absorption (Wer)	156	0.0225	0.1233	-0.2688	0.4147
Absorption interaction (Ier)	156	0.0183	0.0462	-0.0939	0.2278
Nonemployment absorption (Uer)	156	-0.0260	0.0616	-0.1746	0.1582

High school dropouts

Variable	Obs	Mean	Std. Dev.	Min	Max
Population % change (%∆Ler)	52	-0.0510	0.1409	-0.3640	0.4260
Migration inflow (Mer/Ler,2001)	52	0.0759	0.0602	0.0063	0.317
Change in emp. rate (∆NRer)	52	0.0491	0.0316	-0.0194	0.1228
Change in log wages (∆ln wer)	52	0.2948	0.0519	0.2113	0.4682

High school graduates

Variable	Obs	Mean	Std. Dev.	Min	Max
Population % change (%∆Ler)	52	0.2979	0.2212	-0.1433	1.0743
Migration inflow (Mer/Ler,2001)	52	0.1333	0.1259	0	0.5947
Change in emp. rate (∆NRer)	52	0.0556	0.0369	-0.0131	0.16
Change in log wages (∆ln wer)	52	0.2657	0.0286	0.2156	0.3580

College graduates

Variable	Obs	Mean	Std. Dev.	Min	Max
Population % change (%∆Ler)	52	0.2246	0.1947	-0.2746	0.6600
Migration inflow (Mer/Ler,2001)	52	0.0735	0.0619	0.006	0.3228
Change in emp. rate (∆NRer)	52	0.0505	0.0451	-0.0706	0.1224
Change in log wages (∆ln wer)	52	0.2612	0.0404	0.1946	0.3849

Data sources: LFS 2001 and 2006 (all quarters), Census 1991 (for the construction of the instrument, Z), and 2006 MCVL (for wages).
Note: See appendix for the definition of education levels.

Table 2. Actual and imputed immigration flows by education and province

	1			2		
Dependent variable	Migration inflow (Mer)			Migration inflow per population (Mer/Ler,2001)		
Main explanatory variable	Imputed inflow (Zer)			Imputed inflow per population (Zer/Ler,2001)		
Country of origin	*Coefficient*	*(Stdev)*		*Coefficient*	*(Stdev)*	
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%)
Data sources: 2001 and 2006 LFS, and 1991 Census.
Note: 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. All regressions include region and education fixed-effects and use weights. The number of observations is 156. The weights used are $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$

Table 3. First-Stage Regressions

Dependent variable: Population percent change (%ΔLer)

	1		2		3	
$Z_{er}/L_{er,2001}$	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)	
Region f-e	Y		Y		Y	
Robust	Y		Y		N	
Drop small	N		Y		N	
Weights	N		N		Y	
F	56.12		65.21		71.3	
N	156		150		156	

(* significant at 10%; ** significant at 5%; *** significant at 1%)
Data sources: 2001 and 2006 LFS, and 1991 Census.
Note: Each column reports the results from a separate regression, where the dependent variable is $\%\Delta L_{er}$, the change in the size of an (e,r) cell, and the main explanatory variable is $Z_{er}/L_{er,2001}$, the "imputed" migrant inflow. The weights used are $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$

Table 4. Wage Regressions

Dependent variable: $\Delta \ln w_{e,r}$

	1		2		3	
OLS						
$\%\Delta L_{e,r}$	-0.0096		-0.0050		0.0068	
	(0.0167)		(0.0200)		(0.0220)	
High school grads.	-0.0257	**	-0.0284	**	-0.8827	***
	(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						
$\%\Delta L_{e,r}$	-0.0599		0.0331		-0.0095	
	(0.0547)		(0.0684)		(0.0677)	
Region f-e	Y		Y		Y	
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%)
Data sources: 2001 and 2006 LFS, 2006 CSWL, and 1991 Census.
Note: Each column reports the results from a separate regression, where the dependent variable is $\%\Delta w_{er}$, the change in the log daily wage in an (e,r) cell, and the main explanatory variable is $\%\Delta L_{er}$, 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 for details on the construction of the wage variable). The weights used are $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$

Table 5. Employment Rate Regressions

Dependent variable: $\%\Delta NR_{e,r}$

	1		2		3	
OLS						
$\%\Delta L_{e,r}$	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						
$\%\Delta L_{e,r}$	0.0435		0.0884		0.0848	
	(0.0476)		(0.0864)		(0.0630)	
Region f-e	Y		Y		Y	
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%)
Data sources: 2001 and 2006 LFS, and 1991 Census.
Note: Each column reports the results from a separate regression, where the dependent variable is ΔNR_{er}, the change in the employment rate in an (e,r) cell, and the main explanatory variable is $\%\Delta L_{er}$, the percent change in the population of each cell. The weights used are $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$

Table 6. Output Mix (Between-Industry) Regressions

Dependent variable: $B_{e,r}$

All sectors	1		2		3	
OLS						
$\%\Delta L_{e,r}$	0.1428	***	0.1478	***	0.1415	***
	(0.0347)		(0.0410)		(0.0305)	
IV						
$\%\Delta L_{e,r}$	-0.0183		0.2049		0.0668	
	(0.1596)		(0.1349)		(0.0964)	
Only traded sectors						
OLS						
$\%\Delta L_{e,r}$	0.0435	***	0.0370	*	0.0356	**
	(0.0165)		(0.0193)		(0.0154)	
IV						
$\%\Delta L_{e,r}$	0.0335		0.0511		0.0203	
	(0.0355)		(0.0649)		(0.0474)	
Region f-e	Y		Y		Y	
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%)
Data sources: 2001 and 2006 LFS, and 1991 Census.
Note: Each column reports the results from a separate regression, where the dependent variable is B_{er}, the weighted % change in employment by industry in an (e,r) cell at the 2001 factor intensities, and the main explanatory variable is $\%\Delta L_{er}$, the percent change in the population of each cell. A 30-industry classification is used. The weights used are $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$

Table 7. Worker Mix (Within-Industry) Regressions

Dependent variable: $W_{e,r}$

All sectors	1		2		3	
OLS						
$\%\Delta L_{e,r}$	0.5502	***	0.5548	***	0.5392	***
	(0.0367)		(0.0273)		(0.0267)	
IV						
$\%\Delta L_{e,r}$	0.7481	***	0.4518	***	0.6035	***
	(0.1990)		(0.1019)		(0.0844)	
Region f-e	Y		Y		Y	
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%)
Data sources: 2001 and 2006 LFS, and 1991 Census.
Note: Each column reports the results from a separate regression, where the dependent variable is W_{er}, the weighted % change in factor intensities by industry, and the main explanatory variable is $\%\Delta L_{er}$, the percent change in the population of each cell. A 30-industry classification is used. The weights used are $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$

Table 8. Summary of Absorption Channels

Dep. Var.	Nonemployment		Between		Within		Interaction	
OLS								
	0.1702	***	0.1415	***	0.5392	***	0.1491	***
	(0.0224)		(0.0305)		(0.0267)		(0.0230)	
IV	0.1052		0.0668		0.6035	***	0.2244	***
	(0.0715)		(0.0964)		(0.0844)		(0.0742)	

(* significant at 10%; ** significant at 5%; *** significant at 1%)
Data sources: 2001 and 2006 LFS, and 1991 Census.
Note: Each column reports the results from a separate regression, where the main explanatory variable is $\%\Delta L_{er}$, the percent change in the population of each cell. A 30-industry classification is used. All specifications include education dummies and region fixed effects, and use weights $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$

Table 9. Contribution to Between and Within Absorption by Industry

		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 & 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 soc.serv.	0.0262**	-0.0115
16	Domestic serv.	-0.0244	0.0362**

(* significant at 10%; ** significant at 5%; *** significant at 1%)
Data sources: 2001 and 2006 LFS, and 1991 Census.
Note: Each column reports the results from a separate IV regression, where the main explanatory variable is $\%\Delta L_{er}$, the percent change in the population of each cell. A 16-industry classification is used. All specifications include education dummies and region fixed effects, and use weights $((L_{r,2001}{}^{(-1)}) + (L_{r,2006}{}^{(-1)}))^{(-0.5)}$

Appendix

Definition of education groups

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 (2-year, 3-year or longer) or beyond.[32]

Continuous Sample of Working Lives. The CSWL contains information on educational attainment, obtained from local registry data ("Padrón Continuo"). When 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. 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 perfom 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.[33] 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).[34] All remaining individuals are assigned to the intermediate

[32] 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.

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

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

education category.[35] Under these new definitions, the fraction of college graduates in the population for year 2006 is 23%, only 4 percentage points lower than in the LFS.[36]

Construction of 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.

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

[36] 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 A1: Median wages by education.

	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	159723	143568		

Data source: 2006 CSWL.
Note: Daily wage for full-time, year-round workers, by education (in euros).

Table A2: Change in the fraction of the province-education cell whose salary is bottom-coded.

OLS	1	2	3
%ΔLer	-0.0165	-0.0076	-0.0138
	(0.0156)	(0.0082)	(0.0096)
IV			
%ΔLer	-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

Data sources: 2001 and 2006 LFS and 2006 CSWL.