Immigration and productivity: a Spanish tale

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Abstract This paper analyses the extent to which changes in labour composition may affect variation in productivity in Spain. With an original and novel database, we track recently recorded changes in productivity to investigate how the entry of immigrants into the domestic labour market affects productivity. In a few specific situations, our results show that immigrants play the role of environment builders, who bring expertise necessary to fostering productivity and encouraging further improvements in productivity.

1 Introduction

In a European context, the Spanish labour market is often considered as a singular case, distinguished by a few unique features. First, since the beginning of Spain's democratic period, frequent periods of double-digit unemployment rates have occurred, with an important peak that neared 26% in 2013. Second, in the 2000s the Spanish labour

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market hosted an impressive number of immigrants whose share in Spain's total population reached 14.6% (in 2011).[1] In addition, during this same time, Spanish productivity reported deceptive results.

Historically, the most important productivity boosts in Spain have been accompanied by job destruction. Recently, however, the huge immigration inflow seems to have generated a productivity slowdown. In this respect, some studies referring to the period from 1995 to 2006 argue that immigration exerted a significant, negative impact on Spanish productivity because of the occupational composition of employed immigrants as a group (Izquierdo et al. 2010; Kangasniemi et al. 2009).

Other evidence, however, suggests that this claim needs revision. According to the data at hand, we observe an important concentration of immigrants in the service sector, mostly among hotel and transportation jobs, and this sector was least affected during the productivity decline in Spain. Therefore, further research must seek to clarify the trade-off between changes in productivity and labour composition in Spain.

Studying the effects of changes in labour market composition as ways to boost productivity has a long tradition in economic literature.[2] Most of the contributions identify the importance of investing in human capital as a tool to foster productivity. In particular, when referring to micro-level data, the proper organisation of workers' tasks in production processes has principally been identified as an effective device to improve productivity.

In examining plant-level data of US manufacturing industries, Syverson (2004) reports that the productivity values of plants in the 90th percentile are nearly twice as

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high as those in the 10th percentile for a given amount of productive inputs. To explain these results, one needs to interpret the productivity of workers as a combination of their level of human capital in a firm (i.e., the number of employees hired with a superior degree), the organisation of tasks in production processes (Garicano 2000), and the positive spillovers stemming from the social connections among coworkers (Bandiera et al. 2009). As an extension of Garicano (2000)'s work, Caliendo and Rossi–Hansberg (2012) stress the importance of using appropriate hierarchical managerial structures at the firm level, not only to guarantee good productivity but also to spur competitiveness in international markets. These findings indicate that a lack of a suitable managerial strategy—which should include hiring skilled workers to fill strategic vacancies—may cause severe problems for firm performance.

In a similar vein, Boom and van Reenen (2007) investigate the effectiveness of management practices for productivity, including their capacity to build skill-oriented teams. With survey results from a sample of managers in Europe and in the United States, they show how the implementation of proper hiring policies to meet productivity targets and management practices correlates with measures of productivity. Furthermore, this impact is not marginal; good managerial practice entails an increase of roughly 3.2 and 7.5% in productivity in Europe and the United States, respectively.

Studying efficiency in the exploitation of productive resources in shaping productivity is another crucial issue that has been widely investigated with the frontier approach, specifically Data Envelopment Analysis (DEA) and the Stochastic Frontier Approach (SFA). The former technique has been used to assess the extent to which available resources have been used efficiently to generate a set of outputs through deterministic methods of analysis. The latter deals with the possible causes that make the observed production deviate from the theoretical potential production, pinning down the analysis on inefficiency and random disturbances. This deviation is embedded into the structure of the composite error term (Kumbhakar and Lovell 2003). This last approach takes into account the possible inefficient behavior of the unit of analysis (namely, firms or sectors) because of bad practices or lack of good management, for instance. Therefore, improvements in productivity can be recorded either with a reduction of inefficiency in exploiting existing resources or with changes in potential productivity accompanying a shift in the frontier.

In this line of research, technology and human capital are identified as the main driving forces for productivity changes. Kumar and Russell (2002) track the cross-country distribution of labour productivity across time. In a DEA framework, they are able to assess the importance of technological change (rather than technological catch-up or

capital accumulation) in improving production efficiency in rich countries.[3] Similarly, Badunenko et al. (2013) tackle a comparable research question that also includes human capital as an input to production, and the results are substantially confirmed. A further interesting contribution by Maudos et al. (2003) proposes an empirical analysis of the determinants of productivity gains in OECD countries by embracing both an SFA and a DEA strategy. Their results document that a change in human capital is a central factor in boosting productivity in OECD countries through two channels: a higher level of human capital raises labour productivity and, at the same time, affects the rate of technical change. Similar results have also been obtained by Kneller and Stevens (2006) for the specific case of the manufacturing industry in OECD countries by means of the SFA approach. Also under the SFA framework, other studies at a sectoral level not only emphasize the importance of human capital in reducing inefficiency but also stress the importance of managerial skills in achieving this target.[4]

Additional results about the role of human capital in driving changes in productivity emphasize the origin and skills of new hires. This strand of literature assesses that immigrants are beneficial (in economic terms) for host economies (Lewis and Peri 2015). The rationale of this argument stems from two principal ideas. On the one hand, these positive effects happen when foreign-born workers specialize in occupations whose main characteristics are different from the ones in which natives specialize.[5] The efficient relocation of natives and immigrants (on the basis of their correspondent specialization) generates important and sizable effects on total factor productivity (Peri 2012). On the other hand, immigrants can have an impact on productivity through their contribution to technology, by bringing innovation, fueling entrepreneurship or inducing cost-cutting measures at the firm level by substituting imported intermediated inputs (Ottaviano et al. 2015).

In the wake of the current academic debate, our contribution aims at presenting new evidence about the extent to which variations in labour productivity (at the sectoral level) are affected by changes in workforce composition. In particular, we are interested in detecting the potential impact of the entrance of immigrants to the Spanish labour market on changes in labour productivity when considering them as heterogeneous workers in terms of skills.

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[3] Their setting is relatively simple because they consider only three macroeconomic variables: aggregate output, and labour and capital as inputs.
[4] For example, Kirkley et al. (1998) for fishery or Dawson and Dobson (2002) for football associations.
[5] This is the typical trade-off between manual-intense vs. communication-language skills (Peri and Sparber 2009).

Our strategy of analysis is to deal with sector-level data to perform an econometric analysis with a production function in an accounting-style framework.[6] To this end, our empirical strategy involves focusing on the labour composition of new hirings by sector in the different Spanish provinces. To our knowledge, there is no employer-employee database to allow for a micro-level analysis that covers the period in which Spain experienced a huge inflow of immigrants. Therefore, we need to organize (by aggregating at the sector-province level) the available information and match two different sources of data (as detailed in Section 3).Our first contribution, then, is to create an original database by matching data regarding employers and employees at the sector-province level by taking row data from Amadeus (*Sistema de Análisis de Balances Ibéricos*, acronym SABI) and *Muestra continua de vidas laborales* (MCVL CDF version).[7] Our second value added to the current literature is to perform an econometric analysis whose results indicate that hiring selected-skill employees is quite often an effective yet costly program for Spanish firms to improve productivity records. In line with the contemporaneous literature (e.g., Amuedo–Dorantes and de la Rica 2011), our results confirm that the entry of immigrants into the Spanish labour market poses interesting outcomes for Spanish productivity. In some sectors, immigrants bring the knowledge necessary to improve productivity.[8] Unfortunately, the lack of complete micro data at the firm level prevents us from being more precise about firm-level managerial practices in the recruitment process, and so we are inconclusive about the potential efficiency of these practices. However, we are aware of this dimension of the problem. In line with the current literature, in our empirical analysis we deal with sector-fixed effects. In this way, we control for national common hiring practices (by sector) implemented across the whole territory, as one could expect in a highly regulated labour market such as the one in Spain.

The remainder of the paper is organised as follows. In Section 2, we discuss the data and statistics from our database, and in Section 3 we provide evidence about trends in Spanish productivity. In Section 4, we outline our econometric strategy and present our empirical results, and in Section 5 we present our conclusions.

2 Data and statistics

To analyse the impact of changes in labour composition on productivity, we contribute a novel *ad hoc* database that merges data from two pre-existing databases: SABI and MCVL.[9] Since we aim to gather all possible information about changes in the composition of the Spanish labour force, we consider the net flows of people entering the Spanish job market in a given year with both tenure and term contracts.[10] Regarding employees, we consider only workers who are active in firms with at least one employee and therefore use a sample of 500,000 workers, 80% of whom are aged 16–50 years. By nationality, roughly 80% are Spanish, and 20% are immigrants born outside of Spain.[11] From 2005 to 2010, the sectors that reported the most openings were public administration (25–30%), construction (12–18%), retail and tourism (20–25%), and leisure (about 11%). More than 50% of all contracts were full-time term contracts, and the average age of employers was relatively low. According to Rodríguez–Planas and Nollemberg (2014), immigrants are usually hired with fixed-term contracts.

In examining the type of positions filled during the previous hiring, some interesting results emerge. In the provinces of Barcelona and Madrid, an average of 34–38% of contracts during the period filled positions requiring a post-secondary academic degree, whereas from 51 to 58% on average filled positions requiring a higher degree. By contrast, throughout the rest of Spain, more than 64% of signed contracts filled positions requiring a secondary degree, whereas less than 29% required a higher degree. These results indicate a net geographical difference in the labour market, which shows a clear distinction between the requirements that are typical of the two largest metropolitan areas and those everywhere else in Spain. This difference is the product of territorial imbalance in the distribution of economic activities—an imbalance that can affect the areas' potential competitiveness.

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[6] We do not dispose of complete data at the firm level to be able to account for the level of output in accordance with the level and types of inputs. Productivity is measured by (real) sales per worker. Therefore, we are unable to address questions associated with the efficiency of production or selecting DEA or SFA as empirical strategies of analysis.

[7] MCVL provides a rich set of precise individual-level data that can accommodate data in SABI, which hosts data used to calculate productivity at the firm level. Matching these databases is possible by organising the available information by sector (at the two-digit level) and by province. We did so to create our database. To our knowledge, our resultant database is the best tool with which to explore the determinants of changes in productivity by focusing on variation in labour market composition making a difference between native and immigrant workers as well as between skilled and unskilled workers.

[8] These results are in line with the findings in Peri (2012).

[9] More information about the structure of the database merger is available upon request.

[10] For each year and each sector, this net flow is calculated as the difference between people who obtained their first contract or employees who upgraded their positions and people who became unemployed or retired or stopped working indefinitely.

[11] In this study, we focus on six group of immigrants incoming from selected-EU (as a subgroup of the EU15) countries, the rest of EU countries, North American countries, Latin American countries, Asian countries, and African countries.

Table 1 presents some descriptive statistics regarding the most relevant variables as percentage changes that help to sketch some preliminary insights about how changes in labour composition might induce variations in labour productivity (the legend can be found in Table 2). Clearly, the service sector has exhibited more positive productivity variation (intended as changes in labour productivity) than

Table 1 Descriptive statistics (annual variation %)

	Variable	Median	Average	SD	Min/Max	Obs
All	$Varprod_{sht}$	−0.42	0.6	24.3	−75.9/393	5445
	$Spain_{sht}$	59	59.4	18	0/100	5397
	Eu_{sht}	0.6	1.2	2.6	0/100	5397
	$R\text{-}Eu_{sht}$	0.3	1.7	3.9	0/100	5397
	$Asia_{sht}$	0	0.5	1.5	0/100	5397
	$Africa_{sht}$	0.3	1.4	2.6	0/33	5397
	$Latin_{sht}$	2	3.2	4.3	0/100	5397
	N_Americ_{sht}	0	0.1	0.7	0/33	5397
	$High_{sht}$	4.5	11.5	17	0/100	5397
	$Medium_{sht}$	22.5	30	25.4	0/100	5397
	Low_{sht}	67.3	58.7	31	0/100	5397
Industry						
	$Varprod_{sht}$	−0.8	−0.44	19.12	−70.7/235.6	2244
	$Spain_{sht}$	62.7	62.3	16	0/100	2229
	Eu_{sht}	0.5	1.4	3.4	0/100	2229
	$R\text{-}Eu_{sht}$	0.4	2.2	5.2	0/100	2229
	$Asia_{sht}$	0	0.5	2	0/50	2229
	$Africa_{sht}$	0.4	2	3.4	0/33	2229
	$Latin_{sht}$	2	3.3	4	0/50	2229
	N_Americ_{sht}	0	0.2	0.6	0/14	2229
	$High_{sht}$	3.6	6.4	9	0/100	2229
	$Medium_{sht}$	10	14	13.6	0/100	2229
	Low_{sht}	85	79.5	17.5	0/100	2229
Service						
	$Varprod_{sht}$	−0.22	1.34	27.3	−75.9/393	3201
	$Spain_{sht}$	57	57.4	18.7	0/100	3168
	Eu_{sht}	0.6	1.1	2	0/25	3168
	$R\text{-}Eu_{sht}$	0.3	1.3	2.7	0/50	3168
	$Asia_{sht}$	0	0.5	1	0/20	3168
	$Africa_{sht}$	2	0.9	1.9	0/33	3168
	$Latin_{sht}$	2	3.1	4.5	0/100	3168
	N_Americ_{sht}	0	0.09	0.6	0/33	3168
	$High_{sht}$	5.8	15	20	0/100	3168
	$Medium_{sht}$	36.4	41	25.8	0/100	3168
	Low_{sht}	45	44	30	0/100	3168

Notes: See Table 2 for descriptions of the variables

$Varprod_{sht}$ is the annual variation (in percentage) of the value of labour productivity and is calculated at the firm level. From these data, we build a representative value for labour productivity at the sector-province level per year. All other variables are the annual variation (in percentages) of their own share over the total number of new hirings

the industrial sector. Yet, this circumstance is not necessarily due to the effects of job destruction; statistics show that several jobs from 2005 to 2010 were created in the service sector. In reference to median values, statistics also reveal the intense hiring of natives, principally in the industrial sector, whereas job creation for immigrants was more intense in the service sector. In the industry sector, most of the created jobs were positions requiring few skills, whereas positions requiring either a moderate or high level of skills were found in the service sector.[12]

3 Preliminary evidence on labour productivity in Spain

Before analysing the relationship between changes in labour force composition and labour productivity in Spain, it is important to discuss the evolution of Spanish productivity, which is relevant to elucidate the rationale behind this study. From a historical perspective, Nicolini (2011) identifies the problems associated with the dynamics of labour productivity in Spain, from the transition period onward (i.e., since 1977). During this period, the Spanish economy reported record levels of productivity growth with a partial convergence across Spanish regions. However, by the 2000s, the rate of growth declined to record-low values as it became clear that the lack of investment in human capital was partly responsible for this shift. Focusing exactly on the composition of the labour force (especially the entry of immigrants), in this study we seek to map whether changes in productivity are uniformly spread or whether differences appear in order to gather ideas on the way migration inflows could have affected productivity.

To better control for the temporal dimension, we examine the evolution of labour productivity by using stochastic kernel analysis, as introduced by Quah (1997). Briefly, the stochastic kernel can be considered as a conditional probability density, and it maps how a probability density evolves over time. This analytical method involves a generalisation of Markov transition matrices in continuous space to characterise a variable's long-term distribution. The method entails determining the intra-distribution dynamics of a sample of observations by contrasting their behaviour with the representative average of the sample over time. According to the criteria defined by Quah (1997), we plot the dynamics in a two-dimensional graph and interpret the results as follows. The peaks of the distribution—namely, the most concentrated areas—represent the mass

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[12] This result is consistent with findings in the literature. For example, van Ark et al. (2008) report that the growth rate of productivity in the service sector was dominant in countries such as the United States and the United Kingdom from 1995 to 2004.

Table 2 Description of variables

$Varprod_{sht}$	Changes in productivity in sector s and province h at time t with respect to time $t-1$
$Spain_{sht}$	New hirings of workers born in Spain in sector s and province h at time t with respect to time $t-1$
Eu_{sht}	New hirings of workers born in the selected-EU countries in sector s and province h at time t with respect to time $t-1$
$R\text{-}Eu_{sht}$	New hirings of workers born in Europe but not the EU-15 in sector s and province h at time t with respect to time $t-1$
$Asia_{sht}$	New hirings of workers born in Asia in sector s and province h at time t with respect to time $t-1$
$Africa_{sht}$	New hirings of workers born in Africa in sector s and province h at time t with respect to time $t-1$
$Latin_{sht}$	New hirings of workers born Latin America in sector s and province h at time t with respect to time $t-1$
N_Americ_{sht}	New hirings of workers born in North America in sector s and province h at time t with respect to time $t-1$
$High_{sht}$	New hirings of workers with the highest academic degree in sector s and province h at time t with respect to time $t-1$
$Medium_{sht}$	New hirings of workers with a moderate academic degree in sector s and province h at time t with respect to time $t-1$
Low_{sht}	New hirings of workers with a low academic degree or no degree in sector s and province h at time t with respect to time $t-1$ time $t-1$

probability. If the mass is orthogonal to the horizontal axis, then a convergence process (across observations) is present. However, if the mass distributes along the principal diagonal, then the economic system is experiencing low mobility, and relative to the rest of the sample, each observation maintains a position or rank over time. The scope of our exercise is to measure the probability that a firm in a sector in a Spanish province, with a certain level of labour productivity for 1 year, shows any other level of labour productivity for another year.[13]

With data from SABI from 2004 to 2010, we compute the level of productivity by calculating the ratio of the value of sales at constant prices to the total employment at the firm level (conditional on the sector of activity and the province of location), from which we derive a representative measure of labour productivity at the sector-province level.[14] Along with considering the sample in general, we split the sample into two major types of firms: exporters and non-exporters. The period we are referring to covers the years in which an apparent inefficiency in productivity growth took place. Our sample includes firms being active in both 2004 and 2010. For each firm type, real productivity has been computed for 2004 as well as 2010 to derive the joint kernel distribution. The contour plot of each panel of Figure 1 represents cuts that are parallel to the base of the joint kernel distribution (X^{2010} Y^{2004} plan) at equidistant heights (i.e., it connects individual points at the same height). The plots roughly map the individual position of each firm in the general kernel distribution by referring to each firm's productivity in 2004 (along the vertical axis) and 2010 (along the horizontal axis). The reading of the contour

plot must be referred to the position of the mass concentration (namely, the peaks) of observations in the plan. The mass concentration settles along the 45° degree line, which means that the relative position (in terms of productivity) of each firm inside the distribution remains unchanged.

Put differently, each Spanish firm maintained its position in the productivity distribution across time, meaning that its situation in terms of productivity remained unchanged with respect to the rest of the sample. We did not observe any territorial catch-up process at the firm level (still in terms of productivity), especially in the group of non-exporting firms. The relative positions consolidated during a period of important changes in the composition of the Spanish labour market, including the massive inflow of immigrants. This finding, along with the evidence on immigration, implies that the strong concentration of immigrant inflows into Spain—primarily in Madrid, Barcelona, and along the Mediterranean coast[15]—left productivity at the firm level in territories with the greatest migration inflows unaffected. Otherwise, a catch-up process would not be surprising. Consequently, this result provides evidence that in the group of recent hirings, both natives and immigrants share a similar degree of productivity. Therefore, it is not so clear that the productivity slowdown is just a consequence of external immigration.

4 Theoretical background

To bolster our empirical analysis, as in Peri (2012), we consider a simple and general framework that pins down a standard form of aggregate production function for each Spanish province (h), sector (s), in year t as follows:

$$Y_{sht} = A_{st}L_{sht}^{\alpha_s}K_{sht}^{\beta_s}, \tag{1}$$

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[13] This exercise implicitly quantifies the hypothetical average behaviour of each observation with two estimated values as fixed points. In this estimation procedure, defining the law of motion is crucial. Along with most of the literature, we follow the process described by Quah (1997).

[14] More technical details are provided in *[the working paper version available at SSRN.]*.

[15] As discussed in Nicodemo and Nicolini (2011).
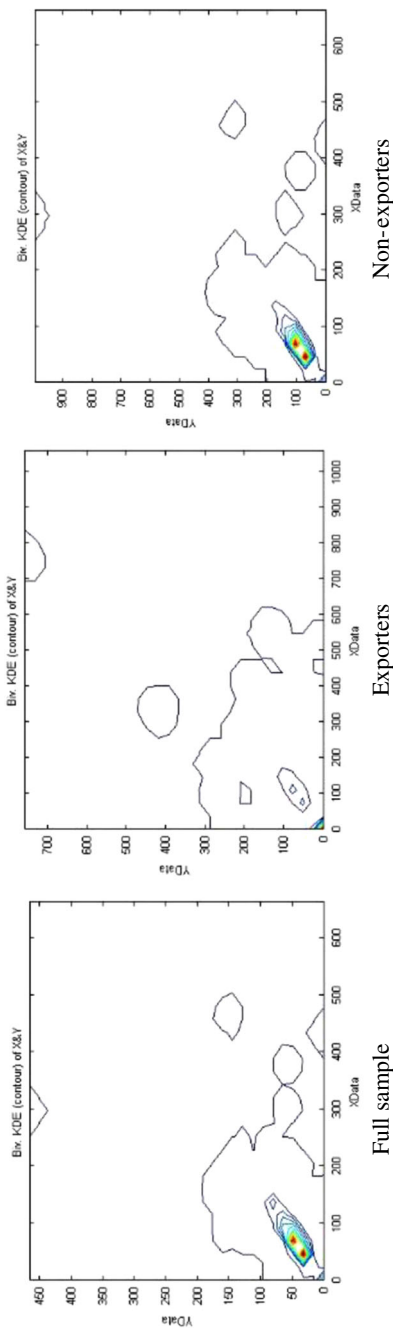
Fig. 1 Stochastic kernel labour productivity (*Source*: SABI; calculus: authors). XData (horizontal axis) = Real value of labour productivity in 2010. YData (vertical axis) = Real value of labour productivity in 2004

where Y_{sht} is the aggregate output at time t obtained by a combination of labour (L_{sht}) and capital (K_{sht}) and A_{st} captures the Hicks-neutral technological progress by sector. The structure of (1) avoids the possibility of input substitution between the different factors of production; rather we stress that they are all fundamental to the production process. The two coefficients α_s and β_s represent the relative share of labour and capital at the sector level in the production function, respectively. In order to keep the setting easy to manage, we assume that (1) displays constant returns to scale ($\alpha_s + \beta_s = 1$).

We also assume that the total number of workers (L_{sht}) is the sum of different groups of people. Each group is characterised by a different qualification (or skills), and all groups are complementary.[16] We therefore consider that the variable L_{sht} is composed of N different groups of (L_{siht}) persons, each of whom brings a skill associated with a specific type of academic degree. In such a production function, more and less educated workers combine their labour inputs. In this sense, the aggregate production function for sector s can be expressed as follows:

$$Y_{sht} = A_{st}\left(\prod_{i=1}^{N} L_{siht}^{\gamma_{sit}}\right)^{\alpha_s} K_{sht}^{\beta_s} \quad with \sum_{i=1}^{N} \gamma_{sit} = 1, \qquad (2)$$

where each coefficient γ_{sit} corresponds to the importance of the contribution of each group of workers to the functionality of production (which may vary across time because of the technological change, for instance). We consider that a full productive process can be completed only with the participation of all groups jointly and each group accounts for a least one worker. The relative importance of each group of workers depends on the sector of production. We consider production to be more intensive in one type of labour if the coefficient γ_{sit} associated with a particular group of workers is larger than those remaining.

From the above, it is easy to identify the marginal effect of a change in each group, which can be written as

$$\frac{\partial Y_{sht}}{\partial L_{siht}} = \alpha_s \gamma_{sit} L_{siht}^{\gamma_{sit}-1}\left(\prod_{i=1}^{N-1} L_{siht}^{\gamma_{sit}}\right)\left(\prod_{i=1}^{N} L_{siht}^{\gamma_{sit}}\right)^{\alpha_s-1}\left(A_{st}K_{sht}^{\beta_s}\right),$$
$$(3)$$

The partial derivative expresses that any change (at time t) in the size of one labour group entails a positive change in output, and the magnitude of this change is proportional to the participation of the group ($\alpha_s\gamma_{sit}$) in the production of the total output. However, this effect is also affected by the group size ($L_{siht}^{\gamma_{sit}-1}$): given $\gamma_{sit} \in (0,1)$, *ceteris paribus*, the larger the group size, the lower the marginal effect.

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[16] In this sense, we aim to introduce Garicano's (2000) ideas into our analysis.

Consequently, even if a group substantially contributes to production (high γ_{sit}), Eq. (3) emphasizes the importance of not exceeding each group size if one wants to preserve the sizable marginal contribution to productivity.

A measure of labour productivity can be obtained by dividing total production by the total number of workers (by sector) L_{sht} at time t. Labour productivity (in each sector) can therefore be expressed as

$$\frac{Y_{sht}}{L_{sht}} = A_{st} \left(\prod_{i=1}^{N} L_{siht}{}^{\gamma_{sit}} \right)^{\alpha_s} \frac{K_{sht}{}^{\beta_s}}{L_{sht}}. \tag{4}$$

Though Eq. (4) displays positive returns in labour and capital, a firm cannot trigger productivity by hiring or investing in inputs limitlessly. At any moment in time, all firms belonging to a sector are subject to budget constraints; their labour productivity outcomes are then subject to cost constraints that we must consider in our empirical exercise.

One way to estimate (4) is to develop it as follows:

$$\log\left(\frac{Y_{sht}}{L_{sht}}\right) = \log A_{st} + \alpha_s \left(\sum_{i=1}^{N} \gamma_{sit} \log(L_{siht}) \right) + \beta_s \log\left(\frac{K_{sht}}{L_{sht}}\right). \tag{5}$$

To fit Eq. (5) to the data, we need to introduce some further working hypothesis. First, we define each group L_{siht} as a combination of workers of different nationalities (M) and skills (E) associated with their educational level. We consider that the skill or educational level indicators are longitudinal with respect to the nationality of the individuals. Then, we assume the existence of e skill-level groups (g) common to all nationalities (M). Therefore, under this hypothesis (and being that $N = M \ x \ e$), L_{siht} can be expressed as

$$L_{siht} = f\left(M_{shgt}, E_{shjt}\right),$$

and without loss of generality, we can embed this working hypothesis in an additive way (in the tradition of the labour economic literature, as in Haltiwanger et al. 1999) in (5) such that it becomes

$$\begin{aligned} \log\left(\frac{Y_{sht}}{L_{sht}}\right) = \quad &\log A_{st} + \underline{\alpha}_1 \left(\sum_{g=1}^{M} \gamma_{sit} \log M_{shgt} \right) \\ &+ \underline{\alpha}_2 \left(\sum_{j=1}^{e} \gamma_{sit} \log E_{shjt} \right) + \beta_s \log\left(\frac{K_{sht}}{L_{sht}}\right). \end{aligned} \tag{6}$$

Having defined labour productivity as a function of labour composition, we devise an empirical strategy to track how variations in labour composition induce variations in labour productivity. We seek to identify how the way in which recruitment practices were applied at provincial and sectoral levels affected the evolutionary trend of labour productivity.

According to the findings in the literature (e.g., Caliendo and Rossi–Hansberg 2012; Peri 2012), one indicator for assessing the presence of positive changes in productivity at the company level is progressive recruiting at the highest level—namely, recruiting high-skill workers to perform tasks that require increasingly specialised qualifications. Translated to our study, we explore the extent to which Spanish companies recruited workers for 'qualified' skill jobs, thereby improving productivity. We also aim to assess whether these positions were filled by immigrants or natives, as well as whether the inflows of immigrants into the Spanish labour market could be detrimental to Spanish productivity.

4.1 Empirical strategy

The entries of our sample exhibit variations in labour productivity at the sectoral and provincial levels in Spain during the period 2005–2010.[17] At first glance, the variation in productivity across sectors and provinces reveals a clearly unequal distribution, with both positive and negative values. Figure 2 displays the shape of such variation.

The variation in labour productivity has a continuous distribution (excluding the outliers on the right-hand side), and two extreme realities are clear: some sectors are performing extremely well, whereas others report discouraging results (Fig. 2). Angrist and Pischke (2009) assess that the study of the determinants for these types of distributions is critical. They may suffer from changes that are not well detected by an analysis of averages,[18] and the quantile regression (QR) is a key tool to control for that possibility.[19] From a strict economic viewpoint, the advantages of using QR lie in the possibility of detecting not only the

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[17] We are dealing with a pseudo-panel (according to the definition by Deaton 1985). We organize the original micro data in cohorts by sector-province for each year. Each cohort is a cross section, and our final pseudo-panel data is the sequence of these cross sections. As for data on labour market variation, we aggregate the correspondent values by sector and province, whereas for labour productivity, we compute the representative value of the (median) productivity by sector-province. In terms of representativeness, although the MCVL is not directly comparable with other data sources, by aggregating our data by sector and province, we are able to replicate the trend of employment growth (at the national level) because it can be extracted from the Labour Force Survey for the period 2006–2010. More details are available upon request.

[18] These types of shapes stem from the mix of several causes that is often hard to summarize as a statistical average. This is exactly the case we are dealing with: our working hypothesis focuses on variation in skills as well as variation in employment composition as determinants (among others) for changes in labour productivity.

[19] Angrist and Pischke (2009) emphasize that when using QR, researchers are interested in shaping a distribution of a continuously distributed random variable with a well-behaving density. In our analysis, to fulfill this condition, we exclude a small number of isolated observations on the top right-hand side of the distribution.
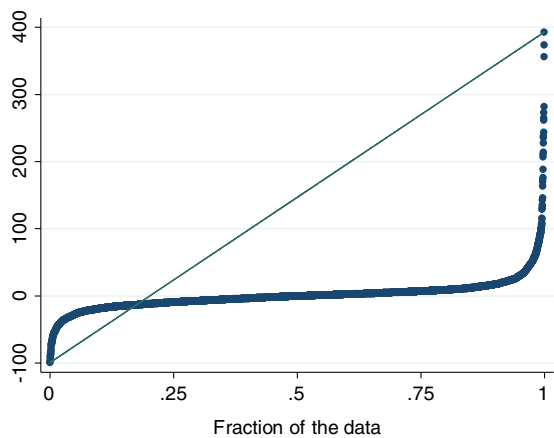
Fig. 2 Distribution of changes in productivity (in %) in the sample (Source: MCVL–SABI, calculus: authors)

determinants of an economic outcome (such as productivity and wages, for instance) but also the way in which these determinants affect productivity inequality as well as, for instance, average productivity.

Compared with the ordinary least squares (OLS) approach, along with providing more robust estimations in the case of heterogeneous data, the QR approach provides richer information about the impact of covariates on the full distribution of data of any particular percentile, yet nevertheless considers overall distribution as well. To interpret the results of the estimations, QR estimates changes in a specific quantile of the response variable caused by a change in the predictor variable. From another angle, QR also overcomes problems in our empirical strategy to select a specific sample of data. We can benchmark our quantile estimation with the outputs of OLS estimations to assess the extent to which QR benefits both the quality of econometric results and our understanding of the economic problems we are negotiating.

To identify the extent to which the recruitment of immigrant workers affects changes in productivity at the sector level, the composition of our database suggests that we can obtain a more complete picture by scrutinising the relationship between the outcome—namely, labour productivity—and the covariates at a different point in the conditional distribution of the dependent variables.

According to the framework described above and by focusing on the classical production function, we can estimate changes in labour productivity that are due to a combination of changes in the labour force and physical capital. In focusing on changes in the composition of the labour force, we can also emphasize the type of new hirings (i.e., natives or immigrants) and their qualifications, which we can track according to the type of contract they sign.

We can therefore perform QR estimations for different quantiles with robust errors obtained via the bootstrap procedure. According to Wooldridge (2002), the bootstrap procedure is a common resampling method alternative to the asymptotic approximations for adjusting standard errors or critical values for test statistics. We can then compare the results with the OLS estimation obtained by performing a regression on the value of changes in productivity against the previous covariates, yet also controlling for time- and sector-fixed effects and clustering by province.[20] If our hypothesis for high heterogeneous data is true, then the QR results must be more informative than those of the OLS.

4.2 Estimations and results

Equation (6) is the testable equation suggested by our theoretical setting. The structure of the available data (namely, providing information on the variation of productivity and its determinants) prevents us from estimating it directly: we need to adapt Eq. (6) to the structure of the data. Therefore, instead of focusing on the relative importance of selected determinants of labour productivity in levels as in (6), we focus on their differences in two moments in time as in (7).

The sequence of the terms on the right-hand side of (7) embeds the importance of taking into account changes not only in the number of workers but also in the composition of the workforce. The variation in the labour force cannot be associated only with the inflow of new hires; it is important to also investigate the variation of the composition of the workforce, making reference to the skill endowment of the new hires, either natives or immigrants.[21]

To be more concrete, we are considering the following equation. It represents the variation of labour productivity against the variation of a selected sample of covariates in the interval $(t-1; t)$:

$$
\left(\frac{Y_{sht}}{L_{sht}} - \frac{Y_{sht-1}}{L_{sht-1}}\right) = \left[\Delta\left(\frac{Y_{sht}}{L_{sht}}\right)\right] = const + \underline{\alpha}_1\left[\sum_{g=1}^{7}\Delta M_{shgt}\right]
$$
$$
+\underline{\alpha}_2\left[\sum_{j=1}^{3}\Delta\log E_{shjt}\right] + \alpha_3\left[\Delta\left(\frac{K_{sht}}{L_{sht}}\right)\right]
$$
$$
+\underline{\alpha}_4\left[\left(\sum_{g=1}^{3}\Delta M_{shgt}\right)x\left(\sum_{j=1}^{2}\Delta\log E_{shjt}\right)\right]
$$
$$
+\delta_t + \mu_s + \varepsilon_{sht}. \tag{7}
$$

---

[20] When applying the clustering-by-province correction, we assume that observations across space are not independent, but sectors belonging to the same province share some institutional or common features. We then correct by clustering to control for these unknown effects.

[21] As discussed in Peri (2012), when considering the skill composition dimension of new hires (in that setting, immigrants), it is possible to assess the potential long-run effect on productivity growth in a typical neoclassical framework.

In Eq. (7), our dependent variable is the change in labour productivity per employee. The index of productivity is the value of sales at constant prices per employee.[22]

Then, our covariates consist of the correspondent variation of a selected group of newly hired employees split into the most important seven ethnic groups (i.e., natives, immigrants from selected-EU countries,[23] the rest of EU countries—including immigrants from Romania—, Asian countries, African countries—including immigrants from Morocco—, Latin American countries, and North American countries), as well as split into three skill categories in accordance with their educational level (i.e., high, medium and low). To capture the physical capital endowment per employee, we also introduce the value of assets per worker, and to consider the constraints entailed by the zero-budget condition, we augment our specification by introducing a value of production cost per employee, which in Eq. (3) represents the cost of producing a unit of goods, normalised against the number of employees.

Furthermore, to control for the contingent features of the local recruiting process, we include selected interaction terms (referring to the three principal groups of workers: natives, selected-EU and Latin American immigrants and the two major relevant skill types—low and high) aiming at accounting for the relative likelihood that workers with specific academic qualifications are hired in the most representative ethnic cohorts of the working population.[24] Finally, we include controls for sector (μ_s) and time dummies (δ_t). Again, Table 2 defines the variables introduced into our estimations.

We begin our empirical analysis with a preliminary exploration using a baseline model (estimated by OLS) in which we aim at determining the impact of our selected variables on changes on productivity.[25]

Unfortunately, our database does not cover all potential determinants of productivity variations, above all when referring to the institutional framework in which contracts come into force. We thereby forgo a great deal of information regarding the contractual relationship, as well as about both the available technology and physical capital. As a result, it is quite likely that the omitted variables may strongly correlate with the explanatory variables and thus cause endogeneity-related problems. In particular, we suspect

the existence of endogeneity problems for the group of natives and selected-EU new employees. These two categories of workers enjoy identical working conditions as established by the European institutional framework of workers' rights and duties, and then they can be assimilated. Evidence points out that EU15 and native workers are employed basically in the same sectors (Rodríguez–Planas and Nollemberg 2014).[26] This institutional framework affects individual working capacity to the point to affect labour productivity outcomes, which in turn influence recruiting strategies. To investigate this endogeneity issue, referring to the baseline OLS results, we run Durbin-WU-Hausman tests for the whole sample by assuming that all hirings for all ethnic groups are endogenous. The statistical results confirm the presence of the potential endogeneity problem [F-stat $(7, 49) = 2.95$ ($p = 0.0115$)]. Then, we proceed to refine our results to isolate the group(s) producing endogeneity. Our tests confirm the outcomes stated in the literature: we need to consider $Spain_{sht}$ and Eu_{sht} as potential endogenous variables. In fact, the correspondent F-stat [2, 49] takes the value 7.88 ($p = 0.0011$), and our theory is confirmed. Furthermore, the test referring to the potential endogeneity of all the remaining group variables for new hirings (by nationality)—after natives and selected-EU groups are excluded—provides a result F(5, 49) = 1.989 ($p = 0.10$) that basically excludes endogeneity for the remaining groups.[27]

Therefore, we need to deal with IV regressions. To implement this type of estimation, we first begin by introducing lagged explanatory variables, as is often suggested in the literature.[28] In addition, as a robustness check, we implement another estimation strategy by running an instrumental variable (IV) estimation in which we instrument our two endogenous explanatory variables following the strategy proposed by Card et al. (2014).

In our first set of estimations, we control for the problem of endogeneity by using lagged explanatory variables. Therefore, we perform the regression for the variation of productivity levels against a set of lagged covariates. In all our estimations, we include time dummies to control for the

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[22] Computed at the 2011 price level.

[23] In this category, we include only new employees incoming from the principal trade partners (Portugal, France, United Kingdom, Italy and Germany). Our idea is to stress the privileged economic connections that exist between these selected partners and Spain in the institutional framework of the (deep) integration process among the EU15 partners.

[24] The interaction terms aim at stressing the ethnic groups of workers with a relevant presence in each of the three skill categories hired in the Spanish labour market. Data at hand suggest limiting the interactions to natives, selected-EU and Latin American immigrants.

[25] Output estimations are available upon request.

[26] During the period we are considering, the EU institutional framework for free labour mobility applies to EU15 members without any reservation, but severe limitations were introduced in Spain (and other EU15 countries) for workers coming from new EU member states, such as Romania or Bulgaria. The Act of Accession of Romania (in 2005) established transition provisions for workers. EU-15 members had the right to deny Romanian workers full access to their labour markets for a seven-year period. On December 22, 2006, the Spanish government approved the adoption of a transition period of two years (starting January 1,2007) before granting EU-free-circulation status to Romanian workers to be hired in Spain. In 2008, the Spanish government decided to stop such a transition period from January 1, 2009, and granted Romanian workers the same status of other workers from other EU countries. Nevertheless, this limitation was retrieved in 2011.

[27] Complete estimation outputs are available upon request.

[28] Refer to Angrist and Pischke (2009) for a short discussion.

changes in the economic cycle for the period we are considering, since it covers part of an expansion phase and part of a recession period. In the same manner, we introduce sector dummies to capture all time-invariant distinguishing features of each sector.

The first set of estimations focuses on the entire sample.[29] Overall, we analyse a sample of more than 5400 observations. First, we perform OLS estimations, after which quantile estimations allow us to focus on particular fractions of data in our distribution. In particular, the lowest quantiles refer to a situation in which changes in productivity show negative variations, whereas the highest ones consider the best-performing sector-province combinations.

Results shown in Table 3 reveal an interesting set of dynamics. Focusing on the OLS estimation controlling for time- and sector-fixed effects (and clustering errors by province),[30] the changes in productivity are positively affected mostly by the hiring of immigrants from selected-EU countries with a high academic degree, followed by the hiring of natives. By contrast, hiring high-skill immigrants from Latin America negatively affects productivity. All of these effects are integrated by other statistically significant determinants in the quantile regressions. The lowest changes in productivity are seemingly being influenced by the hiring of workers born in either the selected-EU countries or Spain. However, it also seems that these firms' organisation of production does not perfectly fit the theoretical findings. For the lowest quantile observations, hiring a qualified or skilled worker is a clear advantage for productivity, whereas hiring a worker with only moderate or low skills is a clear drawback. As for the distribution of productivity variation in the upper quantiles, productivity changes are positively affected by the hiring of selected-EU and native workers—with a magnitude of the effect larger than in the lowest quantile—whereas hiring workers born in Latin America still exerts a negative impact. However, companies belonging to these groups—above all, those ranked with the

highest productivity—are very much concerned with hiring costs, which are more important in the case of skilled workers whose hiring negatively affects productivity changes. This result could be due to the mass effect, meaning that companies have met the required number of high-skill workers for the type of activities they perform and the markets they serve. This situation is reminiscent of one of the recurrent features of the Spanish production system. Both the organisation of tasks at the company level and the operational environment make hiring qualified people extremely costly, even if such strategy is a good one for boosting company productivity and competitiveness.[31]

We can also conceive of a sort of positive discrimination effect in recruiting strategies. While hiring high-skill workers is costly, this action ends up improving productivity in the case of skilled selected-EU workers whose positive impact on productivity changes is greater than that of natives.[32]

The plot of coefficients over quantiles reinforces the previous conclusions (Fig. 3). Hiring skilled workers from Spain and selected-EU countries entails positive changes in productivity, above all in the highest quantiles. By contrast, hiring high-skill Latin American workers reduces the magnitude of changes in productivity for the highest quantile sectors and provinces.

We also run robustness checks for the previous estimations by implementing an IV estimation, according to the strategy proposed by Card et al. (2014). Our preliminary screening clarifies that variables identifying the number of new hirings of natives and selected-EU workers must be considered endogenous. Here, the EU institutional framework makes these two groups of workers quite similar, with respect to their academic credentials, to fill vacancies in the Spanish job market.

Following Card et al. (2014), we instrument these endogenous variables with the corresponding values of hirings for the same categories of workers—namely, selected-EU migrants and natives, respectively—in the same sector in the other Spanish provinces in the same period. The rationale is straightforward. Spatial proximity enhances spatial autocorrelation, and the fact that the provinces share the same macroeconomic or market conditions means that hirings that fill vacancies created in a sector and a province somewhat correlate with those created in the same sector in the other provinces (and always at the same time). Hence, in our empirical IV strategy, we introduce as instruments the total variation of hirings in the rest of the provinces (in the same sector) and their interaction terms with the high- and low-skill hirings. As for the strategy of

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[29] Separate estimations for the industrial and service sectors are available upon request. Note that because of the different time lengths of the SABI and MCVL databases, the effective periods covered by our estimations are 2005–2006 and 2009–2010.

[30] We cannot deal with a purely fixed effect approach by including sector-province fixed effects because of the limited territorial representativeness of the SABI database when including micro firms (firms with at least one employee). Under these circumstances, this database is representative but at the national level, and adopting fixed effects at the province level will imply the introduction of bias in the estimations. Nevertheless, in our cross sections, this is not a stringent limitation. Production strategies are quite similar across all the territories, but they vary across sectors (Nicolini and Artige 2008). Finally, clustering errors by province takes care of common features (such as local environmental or institutional factors at the province level) that have an impact on the activity of all sectors located in a given province. In this way, we manage error correlation.

[31] An extensive discussion appears in Nicolini and Artige (2008).

[32] It is important to note that the 75th and 95th quintiles show the most important positive changes in productivity per worker.

Table 3 Estimation results and lagged covariates for all sectors

	OLS	QR (0.25)	QR (0.5)	QR (0.75)	QR (0.95)
$Constant$	0.859 (0.854)	−15.23 (0.69)***	−10.25 (0.65)***	−5.53 (0.97)***	2.49 (1.69)
$Spain_{sht-1}$	0.0009 (0.014)	0.0028 (0.0009)***	0.0007 (0.0009)	0.0013 (0.0008)*	0.002 (0.002)
Eui_{sht-1}	0.0009 (0.017)	0.053 (0.03)**	0.0002 (0.016)	−0.035 (0.025)	−0.007 (0.04)
$R\text{-}Eu_{sht-1}$	−0.0076 (0.005)	−0.019 (0.006)***	−0.008 (0.007)	−0.002 (0.007)	0.248 (0.018)
$Asia_{sht-1}$	0.008 (0.005)	−0.003 (0.009)	0.004 (0.006)	0.0111 (0.01)	0.011 (0.021)
$Africa_{sht-1}$	−0.008 (0.002)	0.0007 (0.005)	−0.006 (0.004)*	−0.0107 (0.005)**	−0.008 (0.010)
$Latin_{sht-1}$	0.0007 (0.005)	−0.006 (0.005)	0.004 (0.004)	0.004 (0.005)	−0.005 (0.009)
N_Amer_{sht-1}	−0.010 (0.053)	0.004 (0.05)	−0.06 (0.05)	−0.136 (0.05)***	−0.22 (0.088)**
$High_{sht-1}$	−0.005 (0.002)**	0.007 (0.004)*	0.0015 (0.003)	−0.010 (0.003)***	−0.033 (0.006)***
$Medium_{sht-1}$	−0.0013 (0.0007)*	−0.002 (0.0009)**	−0.0015 (0.0007)**	−0.002 (0.0006)***	−0.002 (0.001)**
Low_{sht-1}	7.93e−06 (0.0003)	−0.0008 (0.0005)*	−0.00003 (0.0004)	−3.13e−07 (0.0004)	−0.0004 (0.0008)
$High\_Spain_{sht-1}$	1.06e−06 (4.73e−07)**	−1.51e−06 (1.57e−06)	−2.20e−07 (9.70e−07)	2.21e−06 (1.12e−06)**	7.41e−06 (2.85e−06)***
$High\_EU_{sht-1}$	0.00006 (0.00003)*	−0.00005 (0.00005)	0.00007 (0.00004)*	0.0001 (0.00004)**	0.00025 (0.00009)***
$High\_Latin_{sht-1}$	−7.13e−06 (2.72e−06)**	8.28e−06 (8.53e−06)	−4.05e−06 (5.23e−06)	−0.00001 (6.17e−06)**	−0.00004 (0.00001)***
Low_Spain_{sht-1}	−8.24e−08 (9.03e−08)	−1.58e−08 (1.08e−07)	7.32e−06 (1.03e−07)	−1.05e−07 (8.91e−08)	−2.31e−07 (2.16e−07)
Low_EU_{sht-1}	1.22e−07 (2.42e−06)	−6.39e−06 (5.20e−06)	−2.87e−06 (3.05e−06)	2.81e−06 (4.65e−06)	−4.62e−06 (0.00001)
Low_Latin_{sht-1}	3.64e−07 (6.49e−07)	1.39e−06(7.70e−07)***	2.72e−07 (6.93e−07)	1.06e−07(6.96e−07)	1.43e−06 (1.39e−06)
Ass_empl_{sht-1}	2.34e−06 (6.19e−07)***	2.32e−06 (6.83e−06)	3.14e−06 (7.05e−06)	3.99e−06 (6.28e−06)	6.54e−06 (0.00002)
$Cost\_empli_{sht-1}$	0.328 (0.133)**	0.34 (0.08)***	0.35 (0.097)***	0.29 (0.122)**	0.38 (0.24)
Time dummies	Yes	Yes	Yes	Yes	Yes
Sect. dummies	Yes	Yes	Yes	Yes	Yes
Errors	Clustered (by province)	Bootstrap	Bootstrap	Bootstrap	Bootstrap
R-squared	0.09				
Pseudo R-squared		0.19	0.15	0.13	0.28
Obs	4311	4311	4311	4311	4311

Note: Results for estimations for only industry or service sectors are available upon request.

Dependent *variable*: Variation of productivity (per employee) ($Varprod_{sht}$)

Period: 2005–2010; standard errors in brackets

Other variables not in Table 2: $High\_Spain_{sht}$ (Interaction term: $High_{sht}$ X $Spain_{sht}$), $High\_EU_{sht}$ (Interaction term: $High_{sht}$ X EU_{sht}), $High\_Latin_{sht}$ (Interaction term: $High_{sht}$ X $Latin_{sht}$), Low_Spain_{sht} (Interaction term: Low_{sht} X $Spain_{sht}$), Low_EU_{sht} (Interaction term: Low_{sht} X EU_{sht}), Low_Latin_{sht} (Interaction term: Low_{sht} X $Latin_{sht}$), Ass_empl_{sht} (Assets per employee in sector s and province h at time t with respect to time $t-1$), $Cost\_empli_{sht}$ (Cost per employee in sector s and province h at time t with respect to time $t-1$).

Significance level: * 10 %; ** 5%; *** 1%

Fig. 3 Coefficients for skill native, selected-EU and Latin American hires (see Table 3 for estimations)

Skill Native

Skill selected-EU

Skill Latin American
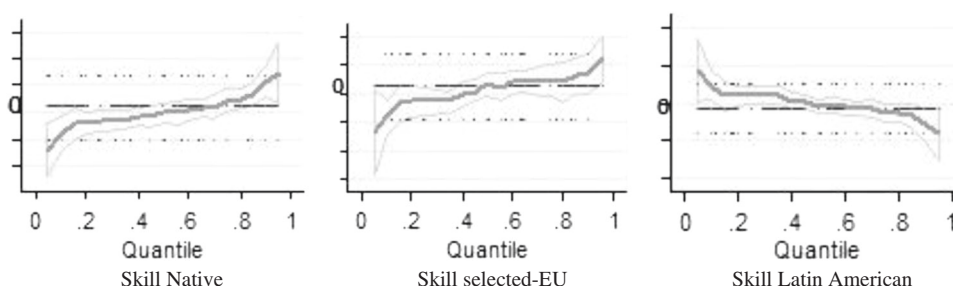
Table 4 IV (2SLS) estimations

	All sectors	Industry	Services
Constant	−6.44 (2.07)***	2.012 (3.45)	14.34 (10.16)
Spain$_{sht}$	0.03 (0.02)	−0.002 (0.002)	−0.002 (0.011)
Eu$_{sht}$	−0.25 (0.3)	0.04 (0.12)	0.04 (0.16)
R-Eu$_{sht}$	−0.06 (0.03)	0.00 (0.00)	−0.004 (0.02)
Asia$_{sht}$	0.03 (0.02)	0.01 (0.01)	−0.01 (0.02)
Africa$_{sht}$	−0.004 (0.01)	−0.007 (0.005)	−0.02 (0.03)
Latin$_{sht}$	−0.02 (0.02)	0.006 (0.012)	0.001 (0.02)
N_Amer$_{sht}$	−0.25 (0.33)	0.032 (0.07)	−0.267 (0.14)*
High$_{sht}$	−0.03 (0.016)**	−0.023 (0.020)	−0.016 (0.008)*
Medium$_{sht}$	−0.01 (0.009)	−0.001 (0.01)	−0.001 (0.006)
Low$_{sht}$	−0.004 (0.005)	0.00 (0.001)	0.002 (0.001)
High_Spain$_{sht}$	3.77 e−06 (3.2e−06)	4.58 e−06 (0.00)	4.54 e−06 (3.06e−06)
High_EU$_{sht}$	0.0003 (0.0002)	0.001 (0.000)**	0.00015 (0.00009)*
High_Latin$_{sht}$	−0.00 (0.00)	−0.0001 (0.000)**	−0.00002 (0.00002)
Low_Spain$_{sht}$	−1.83e−06 (1.24e−06)	1.33e−07 (4.42 e−07)	−5.41e−08 (8.29e−07)
Low_EU$_{sht}$	0.00 (0.00)	−0.00004 (0.00)**	−4.71e−06(0.00002)
Low_Latin$_{sht}$	4.36e−06 (2.88e−06)	3.32 e−06 (1.42 e06)**	2.08e−07 (2.79e−06)
Ass_empl$_{sht}$	7.6 e−06 (7.10 e−06)	−1.42e−06 (0.00)	9.66e−06 (0.00)
Cost_empli$_{sht}$	−1.17 (0.46)**	−3.26 (0.9)***	−0.95 (0.412)**
Time dummies	Yes	Yes	Yes
Sect. dummies	Yes	Yes	Yes
Errors	Cluster (by province)	Cluster (by province)	Cluster (by province)
Weak identification test (Cragg–Donald Wald F *–stat)*	13.740 [b]	19.748 [a]	10.530 [b]
statistics)	13.74*	19.748**	10.53*
R-*squared*	0.06	0.28	0.04
Obs	3230	1341	1739

Note: Dependent variable: Variation of productivity (*Varprod$_{sht}$*)

Period: 2005–2010; standard errors in brackets

Instrumented: *Spain$_{sht}$, EU$_{sht}$* Instruments: *I_Spain$_{sjt}$, I_EU$_{sjt}$, I-High_Spain$_{sjt}$, I-High_EU$_{sjt}$, I-Low_Spain$_{sjt}$, I-Low_EU$_{sjt}$*

According to the Stock and Yogo (2005) weak instrument test (5% significant): [a] means that the weak instrument hypothesis is rejected with 5% maximal IV relative bias and 15% maximal IV size; [b] means that the weak instrument hypothesis is rejected with 10% maximal IV relative bias and 15% maximal IV size.

Significance level: * 10 %; ** 5%; *** 1%

I_Spain$_{sjt}$-1, Instrument: Number of new hirings of workers born in Spain in sector s and in all provinces but h (labelled j) at time *t*-1 with respect to time *t*-2; *I_EUsjt-1*, Instrument: Number of new hirings of workers born in the selected-EU countries in sector s in all provinces but h(labelled j) at time *t*-1 with respect to time *t*-2; *I-High_Spain$_{sht}$*, Instrument: Interaction terms *High$_{sht}$ X I_Spain$_{sjt}$-1*; *I-High_EU$_{sht}$*, Instrument: Interaction terms *High$_{sht}$ X I_EUsjt-1*; *I-Low_Spain$_{sht}$*, Instrument: Interaction terms *Low$_{sht}$ X I_Spain$_{sjt}$-1*; *I-Low_EU$_{sht}$*, Instrument: Interaction terms *Low$_{sht}$ X I_EUsjt-1*

Table 5 IV-quantile estimation results (second step) for all sectors

	QR (0.25)	QR (0.5)	QR (0.75)	QR (0.95)
Constant	−7.01 (1.04)***	−2.269 (0.71)***	2.56 (0.89)***	11.65 (1.98)***
$Spain_{sht}$	0.001 (0.001)	−0.001 (0.002)	0.000 (0.002)	−0.001 (0.004)
Eu_{sht}	0.165 (0.07)**	0.052 (0.044)	−0.07 (0.06)	−0.16 (0.13)
$R\text{-}Eu_{sht}$	−0.017(0.006)***	−0.003 (0.006)	0.000(0.006)	0.02 (0.016)
$Asia_{sht}$	−0.004 (0.008)	0.004 (0.005)	0.002 (0.006)	0.03 (0.017)*
$Africa_{sht}$	0.0003 (0.004)	−0.006 (0.003)*	−0.002 (0.004)	−0.015 (0.009)
$Latin_{sht}$	−0.022 (0.01)**	−0.003 (0.009)	0.007 (0.01)	0.014 (0.02)
N_Amer_{sht}	−0.03 (0.05)	−0.08 (0.04)**	−0.09 (0.52)*	−0.07 (0.10)
$High_{sht}$	0.005 (0.004)	−0.0005 (0.002)	−0.10 (0.003)**	−0.03 (0.007)***
$Medium_{sht}$	−0.0008 (0.0006)	−0.0006 (0.0004)	−0.0008 (0.0006)	−0.001 (0.001)
Low_{sht}	−0.000 (0.0004)	0.0009 (0.0004)**	0.0006 (0.0006)	0.009 (0.001)
$High\_Spain_{sht}$	9.72e−07 (1.49e−06)	3.99e−07 (1.15e−06)	1.74e−06 (1.71e−06)	8.72e−06 (5.2 e−06)*
$High\_EU_{sht}$	−0.0001 (0.00004)**	0.000 (0.000)	0.0001 (0.00)**	0.000 (0.000)
$High\_Latin_{sht}$	4.78 e−08 (6.88e−06)	−3.74e−06 (4.33e−06)	−8.6e−06 (6.37e−06)	−0.000 (0.000)
Low_Spain_{sht}	−8.44e−08 (1.8 e−07)	7.06e−08 (1.82e−07)	−9.9e−08 (1.98e−07)	−2.98e−07 (4.01e−07)
Low_EU_{sht}	−0.00002 (7.39e−08)**	− 8 e−06 (4.62e−06)*	6.43e−06 (6.34−06)	0.0003 (0.000)*
Low_Latin_{sht}	3.37e−06 (1.35e−06)**	6.5e−07 (1.16e−06)	−8.35e−07 (1.33e−06)	−2.58e−06 (3.14e−06)
Ass_empl_{sht}	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
$Cost\_empli_{sht}$	−1.12 (0.20)***	−1.49 (0.15)***	−1.71 (0.16)***	−2.16 (0.36)***
Time dummies	Yes	Yes	Yes	Yes
Sect. dummies	Yes	Yes	Yes	Yes
Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap
Pseudo R-squared	0.24	0.22	0.21	0.36
Obs	4322	4322	4322	4322

Note: Dependent variable: Variation of productivity ($Varprod_{sht}$)

Period: 2005−2010; standard errors in brackets

First step: Errors clustered by province

Instrumented: $Spain_{sht}$, EU_{sht} Instruments: I_Spain_{sjt}, I_EU_{sjt}, $I\text{-}High\_Spain_{sjt}$, $I\text{-}High\_EU_{sjt}$, $I\text{-}Low\_Spain_{sjt}$, $I\text{-}Low\_EU_{sjt}$

Significance level: * 10 %; ** 5%; *** 1%

analysis, we consider the sample as a whole as well as split it into two big sectors: industry and services.

Tables 4–7 show the results of our IV estimations. Our instruments prove to be sufficiently strong: their statistical significance balances out around 5–10%, according to the sector. Then, the model is correctly identified (Table 4). As for the results, the entrance of skilled selected-EU citizens is important for productivity in both the industry and service sectors, whereas hiring skilled native workers is not significant whatsoever. Instead, in the industry sector, hiring low-skill Latin American workers brings small yet positive benefits to improving productivity. This finding could endorse the effectiveness of a good combination of skill–task matching between different categories of workers (in line with Peri's (2012) results for the US market).

In the previous Table 3 estimations, hiring skilled workers entails a cost for the companies, and changes in the cost per employee always place a burden on productivity.

As for IV-quantile regressions (Tables 4–7), the costs of hiring qualified persons are again a concern. Furthermore, for some cohorts of observations, hiring immigrants appears to have been a strategy to foster positive changes in productivity. In particular, productivity changes in the 75th quantile are positively associated with the hiring of high-skill selected-EU workers. By contrast, productivity changes in the 95th quantile in estimations (for all sectors) are driven mostly by the combination of high-skill natives and low-skill selected-EU workers (Table 5). These results exemplify potentially good matches between tasks and skills to enhance productivity. For industry, however (see Table 6), there is evidence of the importance of selective immigrant hiring for high-performing sectors—namely, a preference for skilled selected-EU workers over skilled Latin American workers. Finally, IV estimations for the service sector in Table 7 are not particularly informative. The bulk of their results again confirm the cost of

Table 6 IV-quantile estimation results (second step) for industry

	QR (0.25)	QR (0.5)	QR (0.75)	QR (0.95)
Constant	−5.88 (1.12)***	−1.74 (0.85)**	2.47 (1.16)**	12.10 (2.52)***
$Spain_{sht}$	0.0003 (0.002)	−0.002 (0.003)	−0.003 (0.004)	−0.005 (0.006)
Eu_{sht}	0.132 (0.157)	0.139 (0.164)	−0.70 (0.15)	−0.74 (0.40)***
$R\text{-}Eu_{sht}$	−0.006 (0.007)	−0.008 (0.008)	−0.006 (0.009)	−0.022 (0.015)
$Asia_{sht}$	−0.020 (0.18)	0.003 (0.015)	0.019 (0.016)	−0.15 (0.04)
$Africa_{sht}$	0.007 (0.009)	−0.004 (0.007)	−0.015 (0.008)*	−0.14 (0.018)
$Latin_{sht}$	−0.020 (0.017)	−0.014 (0.016)	0.011 (0.014)	0.08 (0.04)**
N_Amer_{sht}	0.069 (0.078)	−0.004 (0.08)	−0.014 (0.07)	0.27 (0.16)*
$High_{sht}$	0.027 (0.014)**	0.018 (0.015)	−0.02 (0.02)	−0.109 (0.036)***
$Medium_{sht}$	0.005 (0.010)	−0.003 (0.010)	−0.006 (0.010)	0.009 (0.025)
Low_{sht}	0.0002 (0.001)	0.001 (0.002)	0.002 (0.002)	0.002(0.003)
$High\_Spain_{sht}$	−0.00004 (0.00002)**	−0.00002 (0.00002)	0.00003 (0.00003)	0.0001 (0.00007)
$High\_EU_{sht}$	0.0002 (0.0008)	−0.0004 (0.0008)	0.0005 (0.0009)	0.004 (0.002)**
$High\_Latin_{sht}$	0.00006 (0.0001)	0.0001 (0.0001)	−0.0001 (0.0001)	−0.0006 (0.002)**
Low_Spain_{sht}	8.1e−07 (4.91e−07)*	5.98e−07 (5.67e−07)	−5.16e−04(7.71e−07)	−1.26e−06(1.74e−06)
Low_EU_{sht}	−0.00003 (0.00002)	−0.00002 (0.00003)	5.31e−06 (0.00003)	0.00004 (0.00005)
Low_Latin_{sht}	2.31e−06 (2.72 e−06)	7.13e−07 (2.75e−06)	5.86e−07 (2.77e−06)	−1.89e−06(5.69e−06)
Ass_empl_{sht}	2.70e−06 (0.000)	0.00001 (0.00003)	−0.00002 (0.00004)	−5.04e−06 (0.00007)
$Cost\_empli_{sht}$	−1.96 (0.144)***	−1.98 (0.157)***	−2.02 (0.18)***	−2.45 (0.36)***
Time dummies	Yes	Yes	Yes	Yes
Sect. dummies	Yes	Yes	Yes	Yes
Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap
Pseudo R-*squared*	0.30	0.29	0.27	0.34
Obs	1782	1783	1783	1783

Note: Dependent variable: Variation of productivity ($Varprod_{sht}$)

Period: 2005–2010; standard errors in brackets

First step: Errors clustered by province

Instrumented: $Spain_{sht}$, EU_{sht} Instruments: I_Spain_{sjt}, I_EU_{sjt}, $I\text{-}High\_Spain_{sjt}$, $I\text{-}High\_EU_{sjt}$, $I\text{-}Low\_Spain_{sjt}$, $I\text{-}Low\_EU_{sjt}$

Significance level: * 10 %; ** 5%; *** 1%

hiring high-skill workers whose capabilities do not always translate into correspondent proportional increases in productivity.

In sum, a clear finding of our empirical exercise is the generally positive impact in terms of changes in productivity of hiring different groups of immigrants, especially those from a selected-EU country. One possible interpretation of this result involves taking into account the potential externalities stemming from the learning process. In general, worse-performing situations might be associated either with the presence of immigrants who, for cultural or educational reasons, are not as effective in enhancing the efficiency of the production processes or with obsolete productive processes that require updating. To implement such modernisation, it is very likely that hiring foreign workers to provide the required expertise or knowledge background can be a practical way to cultivate a new culture of productivity and support improved productivity.

Empirical results for the 95th quantile of observations definitely stress this finding by revealing a clear, discriminatory hiring process for groups of migrant and native workers to optimise productivity. In this respect, the general perception is that companies believe it necessary to fill vacancies with the most qualified workers—who are not always natives—with a general aim at developing an efficient production process.

5 Conclusion

This empirical contribution proposes an overview of some quantitative evidence about the relationship between the composition of hirings and productivity in Spain. As the literature generally attests, lasting improvements in productivity require important investments in human and physical capital. Spain's current situation suggests that the

Table 7 IV-quantile estimation results (second step) for services

	QR (0.25)	QR (0.5)	QR (0.75)	QR (0.95)
Constant	−25.59 (7.44)***	6.10 (6.79)	18.59 (9.42)**	109.1 (91.54)
$Spain_{sht}$	0.003 (0.002)	−0.012 (0.003)	0.001 (0.002)	0.006 (0.005)
Eu_{sht}	−0.045 (0.069)	0.004 (0.05)	−0.031 (0.07)	−0.158 (0.154)
$R\text{-}Eu_{sht}$	−0.026 (0.014)*	−0.001 (0.014)	0.008 (0.013)	0.062 (0.029)**
$Asia_{sht}$	0.017 (0.010)	0.017 (0.011)	−0.008 (0.013)	0.050 (0.031)
$Africa_{sht}$	0.011 (0.014)	0.006 (0.014)	−0.012 (0.012)	−0.022 (0.03)
$Latin_{sht}$	−0.014 (0.011)	−0.003 (0.012)	−0.009 (0.013)	−0.013 (0.024)
N_Amer_{sht}	0.049 (0.07)	−0.036 (0.067)	−0.126 (0.07)*	−0.137 (0.162)
$High_{sht}$	0.006 (0.003)*	−0.001 (0.003)	−0.0106 (0.004)***	−0.32 (0.009)***
$Medium_{sht}$	−0.0006 (0.0006)	−0.0001 (0.0007)	−0.0006 (0.0011)	−0.003 (0.002)*
Low_{sht}	0.0007 (0.0006)	0.0004 (0.0005)	0.001 (0.0007)	−0.0005 (0.002)
$High\_Spain_{sht}$	−8.71e−07 (1.63e−06)	−3.49e−07 (1.64e−06)	2.93e−06 (2.51e−06)	8.98e−06 (6.84e−06)
$High\_EU_{sht}$	−0.00008 (0.00005)	0.00006 (0.00004)	0.00005 (0.00006)	0.0001 (0.0002)
$High\_Latin_{sht}$	−7.27 e−06 (7.04e−06)	−1.5e−07 (6.24e−06)	−9.65e−06 (9.26e−06)	−0.00003 (0.00003)
Low_Spain_{sht}	3.14e−07 (2.85e−07)	1.23e−07 (3.09e−07)	−3.12e−07 (3.51e−07)	6.91e−07 (7.40e−07)
Low_EU_{sht}	−2.47e−06 (7.13e−06)	−4.21e−06(5.06e−06)	3.89 e−06 (6.53e−06)	0.00003 (0.00002)
Low_Latin_{sht}	−2.42e−06 (1.72e−06)	−3.05e−07 (1.78e−06)	8.43e−07 (2.05e−06)	−1.26e−07 (4.15e−06)
Ass_empl_{sht}	0.00001 (0.00002)	0.00002 (0.00002)	0.00001 (0.00004)	0.0003 (0.00009)
$Cost\_empli_{sht}$	−0.92 (0.24)***	−1.24 (0.19)***	−1.61 (0.19)***	−2.09 (0.52)***
Time dummies	Yes	Yes	Yes	Yes
Sect. dummies	Yes	Yes	Yes	Yes
Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap
Pseudo R-squared	0.23	0.16	0.16	0.29
Obs	2540	2545	2545	2545

Note: Dependent variable: Variation of productivity ($Varprod_{sht}$)

Period: 2005–2010; standard errors in brackets

First step: Errors clustered by province

Instrumented: $Spain_{sht}$, EU_{sht} Instruments: I_Spain_{sjt}, I_EU_{sjt}, $I\text{-}High\_Spain_{sjt}$, $I\text{-}High\_EU_{sjt}$, $I\text{-}Low\_Spain_{sjt}$, $I\text{-}Low\_EU_{sjt}$

Significance level: * 10 %; ** 5%; *** 1%

entry of skilled workers into the job market is not always profitable or feasible at the firm level. Even if having a productive environment is important for making skill hiring efficient, current Spanish firms seem more motivated to implement cost-reduction strategies.[33] Our results show that hiring selected groups of immigrants brings specific skills to the labour environment that can boost productivity. The particular economic situation in the 2000s supports this process. During times of labour shortage (as happened during the economic expansion period up to 2008), employers had to implement the most suitable managerial strategies for addressing the need to fill job vacancies. In this line, the Spanish public administration implemented the Strategic Plan for Citizens and Integrations (2006–2009), which was revealed to be an important success story from both an economic and integration viewpoint. This plan was a joint action between entrepreneurs and administrative bodies (at both the national and local level). The recruitment process was run on skill demand, and this new process favoured the best matching between the type of vacancy and the most appropriate workers (Corcoran 2006). This policy is part of a broader project common to other European countries (for instance, France) to facilitate the entry of skilled individuals or individuals possessing skills that are scarce in local labour markets. Evidence referring to the period 2006–2010 emphasizes that the share of college-educated foreign-born workers is higher than the native one in Spain. In line with other European countries, Spain implemented national policies to attract skilled or talented workers. As in France, Spain adopted a scheme to allocate special work permits (de la Rica et al. 2014). In 2007, this action was supported by the creation of an ad hoc special unit (*Unidad de Grandes Empresas y Colectivos Estratégicos—UGE-CE*) charged with speeding up the issue of the required administrative permits to firms aiming at hiring skilled workers that were not eligible to enjoy the

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[33] As in the survey conducted by Nicolini and Artige (2008).

favourable conditions granted to EU15 citizens. The rationale underlining this initiative is that the recruitment of the most suitable candidates without any institutional restriction is expected to be a valuable strategy for implementing productivity performance.

More generally, the inflow of qualified and skilled immigrants filling suitable positions that match their educational background also promotes learning inside firms and thereby creates an environment suitable for natives to join. In addition, by means of peer effects, positive externalities may spill over to the rest of the labour force, hence enhancing the general positive effect on productivity performance.

Nevertheless, to be more precise about the potential impact of recruitment strategies, we need to perform further and more detailed investigations. To this end, new databases at the firm level should be developed to provide quantitative policy recommendations. It remains particularly important to use proper employer–employee databases to overcome limitations in the matching processes performed in this study. From another angle, it could also be interesting to conduct a comparative study of other European countries to examine the specific features of the Spanish situation, as well as those that Spain shares with other European countries.

Conflict of interest The authors declare that they have no conflict of interests.

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