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DOES IMMIGRANT DIVERSITY AFFECT PRODUCTIVITY?

THE SPANISH EXPERIENCE

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Abstract

The consequences of the massive waves of migration in recent years have attracted a growing amount of attention in the field of economics. Traditionally, concern over this matter has focused on the possible effects of replacing more expensive native workers with a cheaper workforce made up of immigrants. However, recent literature points out that this evaluation may be incomplete, as it ignores the potential benefits derived from a greater cultural diversity related to immigration. The aim of this work is to analyse the impact of migration diversity on productivity at a regional level for the specific case of Spain. To do so, we have based our research on three different diversity indexes, as proposed by Kemeny and Cooke (2018) and Alesina *et al.* (2003). The model is estimated by using instrumental variables techniques taking into account the potential simultaneity between migration diversity and productivity. The results confirm the positive influence of a greater diversity of immigrants' birthplaces on workers' productivity in Spain. Our findings reveal that a higher rate of young and skilled labour also encourages productivity.

Keywords: birthplace diversity, immigration, productivity, Spain.

JEL Classification: J61, C26, O4, R23.

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1. INTRODUCTION

Coinciding with the Spanish economic “boom”, the entry of migrants into the country was absolutely remarkable. Spain went from having a total foreign population of 2% in the year 2000 to approximately 12% in 2011 (Martí Romero, 2015). The economic expansion and the creation of new jobs attracted a massive number of immigrants seeking employment opportunities (Alamá, Alguacil and Bernat, 2014). For nearly a decade, Spain’s GDP grew yearly by an average 3.9%, which meant a drop in the unemployment rate from 20.6% in 1997 to 8.2% in 2007. However, the economic crisis that started in 2008 and manifested in Spain primarily as an employment crisis led to a radical change in the Spanish migration model (Parella and Petroff, 2014). According to the Residential Variation Statistics, in 2013, for the first time, the number of immigrants was less than in the previous period (“inflation point”). The number of citizens of foreign origin, however, remained significantly high, as in 2016 immigrants represented approximately 10% of the total population of the country.

Also linked with this shift were the changes in the nature and distribution of immigrants across regions. With the crisis, the proportion of immigrants coming for economic reasons became less relevant and the weight of immigration from developed countries motivated by socioeconomic reasons increased (Arango *et al.*, 2009; Alamá, Alguacil and Bernat, 2014). Similarly, coastal provinces (including Cantabria and Andalusia) played a more important role in attracting immigrants (Alamá-Sabater, Alguacil and Bernat-Martí, 2017). The variety of immigrants’ countries of birth also differed by region, with Autonomous Communities (AC from now on) such as Madrid and Catalonia, the Valencian Community and Andalusia having a higher diversity of immigrants’ birthplaces. In the case of Madrid and Catalonia, this was probably due to the large supply of work available in different sectors and with different skill requirements. For the Valencian Community and Andalusia, the relevance of both the tourist sector and intensive agriculture, together with the good weather, may explain this higher diversity of immigrants in terms of country of origin (Otero, 2010). The aim of this work is to analyse how this migrant diversity affected worker productivity across Spanish regions during the period from 2008 to 2016.

Given the recent concern in the European political debate about the effects that the entry of new residents can have on domestic labour markets, it seems relevant to investigate how greater birthplace diversity can influence labour productivity. The literature in this respect suggests that there may be a positive correlation between immigrant diversity and worker productivity (Alesina *et al.*, 2003; Ottaviano and Peri, 2006; Kemeny and

Cooke, 2018). For Lewis and Peri (2014), immigrant diversity can increase productivity by enabling the combination of different skills, ideas and perspectives. According to Hong and Page (2004), diversity of human capital increases creativity and helps members to solve problems and generate new ideas. Conversely, other authors argue that the relationship between immigrant diversity and productivity may be ambiguous. For instance, Lee (2013), who examined the cultural diversity within the groups of workers of a company, argued that this group-level diversity may lead to lower confidence among workers and poor communication between people, either by discrepancies in the language, misunderstandings or discriminatory attitudes, as some individuals may subconsciously favour members of their own nationality.

Empirically, we contribute to this literature in several ways. First, for the first time, three immigrant diversity indexes, as proposed by Kemeny and Cooke (2018) and Alesina *et al.* (2003), have been implemented for the case of Spain to analyse the connections between migration diversity and productivity. We did so by focusing on the years after the economic crisis that began at the end of 2007, thus taking into account the changes that occurred in the immigration patterns with the new macroeconomic scenario. Second, we estimated the model by two-stage least squares (2SLS) using Instrumental Variables (IV) regression techniques. As previously mentioned by the literature, the most productive regions can also be those that attract more immigrants from different backgrounds (Ottaviano and Peri, 2006), thus giving rise to a potential endogeneity problem. To deal with this, we based our work on Gagliardi (2015) and Ottaviano and Peri (2006) and calculated the “predicted” change in the number of immigrants in each AC during the period analysed as the instrumental variable. Finally, we tested the robustness of our results by estimating an additional model in which workers’ productivity was proxied by the wages of the total national and foreign population, instead of considering only the wages of nationals. To do so, we used a database on the 17 Spanish Autonomous Communities between 2008 and 2016 from the Spanish National Statistics Institute (INE) and the Ministry of Education, Culture and Sports.

The results obtained are in line with those from previous studies, confirming the positive and significant effect of greater diversity of immigrants’ birthplace on worker productivity. Moreover, this result holds for both the total population and considering only the wages of nationals. These findings are robust to the inclusion of other control variables, such as education and share of immigrants that come from countries with a high or very high level of human development.

The rest of the paper is organized as follows. Section 2 reviews the literature on the economic consequences of migration diversity. Section 3 shows the construction and analytical decomposition of our migration diversity indexes. The next section, Section 4, provides some stylized facts analysing the relation between immigration diversity and productivity for the Spanish case. Section 5 explains the data source and the econometric model, including the description of the variables and the theoretical model used to design and interpret our estimation strategy. Section 6 presents the estimation results. Finally, Section 7 concludes with a policy discussion and suggestions for future research on the topic.

2. IMMIGRATION DIVERSITY AND PRODUCTIVITY: AN OVERVIEW OF THE LITERATURE

The economic effects of immigration have been widely analysed in many empirical papers. Motivated by a growing concern in modern economies about a substitution effect from more expensive native workers to cheaper immigrant workers, primary attention has been paid to the impact of immigration on the labour market of destination regions. Questions like whether immigrants harm or improve the employment conditions and opportunities of native workers have been analysed in depth in the literature, with evidence yielding a mixed and confusing set of results (Borjas, 2003). For some authors this ambiguity indeed reflects a non-significant effect of migration on the receiving economy (Smith and Edmonston, 1998; Friedberg and Hunt, 1995).

After the recent waves of immigrants to the OECD countries, migration has become a phenomenon that concerns many countries in the developed world (Boubtane *et al.*, 2015). Therefore, it is not surprising to find that a significant number of studies that analyse this phenomenon focus on the macroeconomic effects of this movement using time-series or panel data analysis. For Ortega and Peri (2009), for instance, migration in the OECD countries during the period 1980 to 2005 increased employment and capital stock, although the effects on total factor productivity are negligible. Boubtane *et al.* (2013), however, showed a significant relationship between immigration and GDP per capita for 22 OECD countries over the period 1987-2009. Using time-series analysis, Morley (2005) found a long-run causality from GDP per capita to immigration but not the other way round. Other authors, such as Zorlu and Hartog (2005), Longhi *et al.* (2010) and Ottaviano and Peri (2012) have considered that the work offered to natives involves jobs in which they could be replaced by immigrants and so, as a consequence of the arrival of large numbers of immigrants, wages can be reduced.

Table 1. Overview of studies on the impact of migrant diversity on economic performance.

Authors	Year of Publication	Focus	Data	Years	Diversity Measure	Results
Alesina, Devleeschauwer, Easterly, Kurglat, Wacziarg	2003	Effects of ethnic, linguistic, and religious heterogeneity on the quality of institutions and growth.	190 countries	Data from different sources between 1960-1995	Ethnic, linguistic, and religious fractionalization	Ethnic and linguistic fractionalization variables, more so than religious ones, are likely to be important determinants of economic success, both in terms of GDP growth, other measures of welfare and policy quality and the quality of institutions.
Hong and Page	2004	Analyse if groups of diverse problem solvers can outperform groups of high-ability problem solvers	Three different group composition (Result of computational experiments)	-	Demographic characteristics, cultural identities and ethnicity, and training and expertise	When selecting a problem-solving team from a diverse population of intelligent agents, a team of randomly selected agents outperforms a team comprised of the best-performing agents.
Ottavino, Peri	2006	Economic consequences, specifically productivity, of the growing diversity of American cities	160 Standard MSA's from USA	1970-1990	Percentage of foreing-born and a fractionalization index	Higher wages and higher rents for US natives are significantly correlated with higher diversity
Wadhwa, Saxenian, Rissing and Gereffi	2008	Relation between highly skilled immigrants to USA engineering and technology-related industries nationwide.	28.000 engineering and technology companies in USA	1995-2005	Birthplace of the key founders of the companies	Skilled immigrants have contributed significantly to the USA economic growth over time as those firms in which the founders were both skilled immigrants and Americans contributed substantially both to job and wealth creation in the USA.
Borjas, Doran	2012	Effect on productivity on those mathematicians whose research overlapped with that of the Soviets.	Works published by mathematicians in the USA in one of the 63 different fields in which at least one author of the Soviet Union.	1970-1989	Mathematicians in the USA born in the Soviet Union.	Those mathematicians whose research programs involved Soviet researchers suffered a reduction in productivity and their publications were considerably reduced.
Alesina, Harnoss and Rapopot	2013	Impact on the economic prosperity of the birthplace diversity	Immigrantion data from 195 countries	1990-2000	Birthplace diversity index	The diversity of skilled immigration relates positively to economic develpment
Bakens, Mulder and Nijkamp	2013	Impact of cultural diversity on local economies	61.738 individual workers/homeowners	1999-2008	Cultural fractionalization	There is a negative impact of cultural diversity on local housing markets likely driven by a causal effect between the presence of immigrants and neighborhood quality that outweighs a positive effect of immigrant-induced diversity in consumption goods.

Source: Developed by author.

Table 1 (cont). Overview of studies on the impact of migrant diversity on economic performance.

Authors	Year of Publication	Focus	Data	Years	Diversity Measure	Results
Gagliardi	2013	Effect of an increase in the stock of human capital due to skilled immigration on the innovative performance of recipient economies.	211 british firms in two periods	2002-2004 and 2004-2006	British travel to work areas (TTWAs) as key to address the impact of immigration	Those areas experiencing the most inflows of skilled immigrants are those benefiting from the availability of these new sources of individual incorporated knowledge.
Lee	2013	Two effects: a firm effect, with diversity at the firm level improving knowledge sourcing or ideas generation, and a city effect, where diverse cities helping firms innovate.	2.223 SMEs in UK	2004, 2005	Share of the members or directors of companies that were born outside the United Kingdom	Average city diversity is unimportant compared to firm level diversity. Diverse firms in London tend to innovate more while those in other large cities innovate relatively less.
Longhi	2013	Impact that cultural diversity has on individual wages in England	353 English districts	2002-2007	Ethnic fractionalization	Cultural diversity is positively associated with wages, but only when cross-section data are used, while panel data estimations show no impact of diversity.
Lewis and Peri	2014	Effect that immigration has on urban and regional economies focusing on productivity and labor markets.	Depending on the estimation (for USA): 284 Metropolitan, 50 states, 333 occupations or seven schooling groups.	2011	Immigrants' share of employment	Immigration is associated with higher wages and with higher productivity as it induces natives to specialization in more complex jobs which complement immigrants' skills.
Trax, Brunow and Suedeskum	2015	Effect that cultural diversity has on total factor productivity	11.343 establishment-year observations (7.241 manufacturing and 4.102 service observations)	1999–2008	The share of foreigners in a plant of total workforce and cultural fractionalization	Larger share of foreign workers (either in the establishment or in the region) does not affect productivity, but there are spillovers associated with the degree of fractionalization of the group of foreigners into different nationalities.
Bove and Elia	2017	Relation between cultural diversity and economic growth	Migrant stock data from 135 countries	1960-2010	Index of fractionalization and polarization	Both indices have a distinct positive impact on real GDPpc. The effect of diversity seems to be more consistent in depeloping countries.
Kemeny and Cooke	2017	Effect of immigrant diversity on productivity. Diversity impact at both city and workplace scales.	Employer–employee data from 29 states of USA	1991-2008	Fractionalization index, Entropy index, Alesina index	Immigrant diversity in USA cities and workplaces has an independent positive influence on workers productivity. Moreover, the authors conclude that spillovers from imigrant diversity are consistent across workers occupying different positions in the labor market.

Source: Developed by author.

In recent years, and probably motivated by the greater availability of data, a new perspective, focused on the heterogeneity of immigrants, has been incorporated into this debate, namely, the possibility that greater diversity might have positive effects on worker productivity in destination markets. In Table 1, we present a detailed list of papers that analyse the impact of immigrant diversity on economic performance.

According to this literature, people born in different countries complement each other in the labour market because immigrant diversity could increase productivity by enabling the combination of different skills, ideas and perspectives. The seminal paper on this matter is Ottaviano and Peri (2006). By using panel data from different American Metropolitan Statistical Areas (MSAs) through cultural heterogeneity indexes, these authors confirmed the positive impact of immigration in productivity. The fractionalization index calculated by Ottaviano and Peri (2006) had previously been used by Alesina *et al.* (2003), who built a Herfindahl index of population diversity based on people's birthplaces to determine the relationship between diversity migration and productivity. However, this index has some limitations. According to Alesina *et al.* (2013) and Kemeny and Cooke (2018), it can be biased by the presence of a larger proportion of immigrants in a region. To overcome these limitations, we used two additional indexes: the Entropy Index, first used by Taagepera and Ray (1977), and the Alesina Index, proposed by Alesina *et al.* (2013).

Other authors that highlight the favourable effect of immigrant diversity in terms of productivity and wages are Kemeny and Cooke (2018) and Bove and Elia (2017). The first found that urban immigrant diversity produces positive and nontrivial spillovers. Similarly, Bove and Elia, after studying the diversity of immigrants through indexes of fractionalization and polarization for different countries in the period between 1960 and 2010, claimed that there is a positive effect between immigrant diversity and greater GDP growth per capita, especially in developing countries. For some authors, like Wadhwa *et al.* (2008), this positive correlation is further magnified if only skilled immigrants are considered.

Although, as mentioned above, many empirical works emphasize the possibility of a positive relationship between migration diversity and productivity, the evidence on this matter still remains quite ambiguous. For instance, Longhi (2013) argued that the positive correlation between diversity in English Local Authority Districts and workers' wages found in cross-sections disappears when we consider panel estimations. Other works find a negative influence of diversity in productivity, thus contemplating the relationship between natives and foreigners as more of a substitution than of a complementary nature. According to this literature, cultural diversity at the group level may lead to lower confidence among workers and poor communication between people, due to discrepancies in the language, misunderstandings or discriminatory attitudes, as some individuals may subconsciously favour members of their own nationality (Lee, 2013). Borjas and Doran (2012) claimed that researchers whose mathematical research programmes included Soviet researchers underwent a reduction in productivity and significantly reduced their number of publications.

Related to this approach are also those works that analyse the spillovers of migration diversity in terms of innovation, ideas generated and economic performance. According to Lewis and Peri (2014), the evidence suggests that immigration induces natives to specialize in more complex jobs, which complements immigrants' skills, and that it induces higher levels of innovation, both of which may contribute to the observed impacts on productivity. Using data from more than 200 British firms, Gagliardi (2015) showed how an increase in the stock of human capital due to the arrival of skilled immigrants fosters innovation, giving rise to an increase in the level of knowledge which is accessible to local firms through the labour market. Similarly, for Hong and Page (2004), the diversity of human capital increases creativity and helps members to solve problems and generate new ideas.

Finally, an issue that has been underexplored within this literature is whether highly productive workers have a particular preference for diversity (Kemeny and Storper, 2012; Moretti, 2013). If that is the case, there might be a problem of reverse causality and endogeneity, since more productive regions can also be the ones that attract more immigrants from a wider range of nationalities. As an exception, we can mention the following studies that analyse the relationship between diversity migration and labour productivity considering the possibility of a reverse causality: Bakens *et al.* (2013), Trax et al. (2015) and Kemeny and Cooke (2018). In this paper, we seek to contribute to this strand of the literature by investigating to what extent greater immigration diversity influences worker productivity in Spain at a regional level, taking other relevant factors and a potential reverse causality into account.

3. MEASURING IMMIGRATION DIVERSITY

To measure the diversity of immigrants, we use several indexes based on the Herfindahl diversity index[1]. In particular, this work uses those indexes proposed by Kemeny and Cooke (2018) in which the diversity of immigrants is measured according to their place of birth: Fractionalization Index (FI), Entropy Index (EI), Alesina Index (AI). Each index captures diversity in a different way, giving more weight to the share of immigrants or to the variety (number of birthplaces).

Before explaining the indexes, a few considerations must be discussed, as Alesina *et al.* (2013) suggested. First, there is a limitation because illegal immigration is not captured in the statistical data measured. Second, diversity has been defined according to the place of birth of the immigrants and, therefore, according to this definition, a small child who immigrates with his or her parents will be considered an immigrant despite having received the education and culture of the host country.

Most of the empirical studies on migration diversity employ the Fractionalization Index. This index, based on the Herfindahl Index, measures the probability that two migrants, randomly selected from the population of a specific host region, were born in different countries. Specifically, this index can be written as:

$$Fractionalization_j = 1 - \sum_{r=1}^{R} s_{r_j}^2 \qquad (1)$$

where s ($0 \leq s \leq 1$) is the proportion of residents in an AC who were born in country r and R represents the maximum number of countries captured in the population. In our case R=114 including natives. When the index is close to zero this indicates low diversity, while the closer it is to one, the higher the heterogeneity of the population of the AC will be, having as its maximum value $\left(1-\frac{1}{R}\right) = \left(1-\frac{1}{114}\right)$.

Several authors, like Alesina *et al.* (2003; 2013), Ottaviano and Peri (2006) and Bove and Elia (2017), have also used the FI as a measure of diversity.

As an alternative to the FI, Kemeny and Cooke (2018) used the Entropy Index, which has also been used by authors like Wang (2012), Sturgis *et al.* (2014) and Wright *et al.* (2014). Entropy, as a mathematical construct, was first introduced into social sciences by Theil (1967, 1972) to solve political problems involving the distribution of seats and

[1] As Parrotta et al. (2012) mentioned, the Herfindahl index allows us to combine two measures within one index: the “richness”, or number of categories within the region, and the “equitability”, or evenness of the individual categories.

votes among various parties and then by Taagepera and Ray (1977) as an index of concentration. Like the Fractionalization Index, it measures the probability that two randomly selected individuals were born in different countries. However, for these authors this index provides a more accurate measure of diversity when the groups of different nationalities are of different sizes.

$$Entropy_j = -\sum_{r=1}^{R} s_{rj} \cdot \ln(s_{rj}) \tag{2}$$

The Entropy Index reaches its maximum value when $Entropy_j = \ln(R)$, when the population is totally heterogeneous. Conversely, EI reaches its minimum value, when $Entropy_j = 0$, which implies complete homogeneity or no diversity, with all population members in the same group.

Finally, we use the Alesina Index (Alesina *et al.*, 2013), as proposed by Kemeny and Cooke (2018). As these authors explained, the FI can be biased by the presence of a large proportion of immigrants in a region even if those immigrants do not come from a wide range of countries of origin. That is, this index gives greater weight to depth than to breadth. To overcome this limitation, Alesina *et al.* (2013) suggest measuring diversity strictly among those born abroad in a given place, instead of capturing heterogeneity among all individuals: natives and immigrants. Namely, it captures all residual diversity from differences between immigrants only.

$$Alesina_j = \sum_{r=2}^{R} \left[\frac{s_{rj}}{(1 - s_1)} \cdot \left(1 - \frac{s_{rj}}{(1 - s_1)}\right)\right] \cdot (1 - s_1)^2 \tag{3}$$

where s_1 indicates the share of natives.

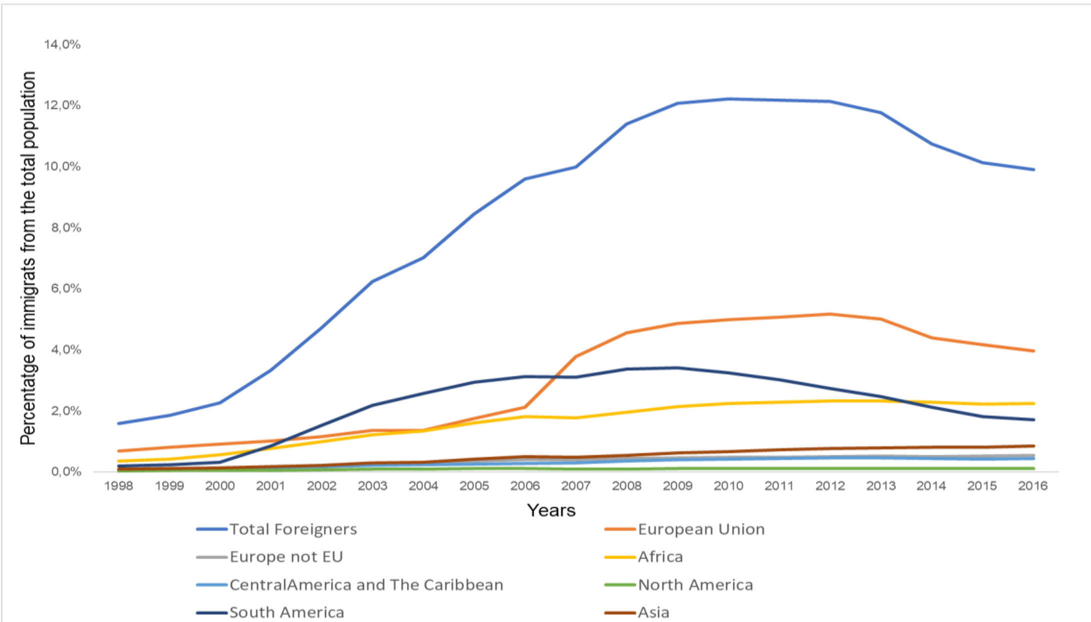
In contrast to the first two indexes, which are estimated for the entire population, the AI will not be influenced by the large number of natives in each AC as it uses a measure of immigrant-only fractionalization. This approach is able to solve the extent to which the effects arise due to the sole presence of foreign-born individuals, instead of its heterogeneity. Thus, unlike indexes estimated over the entire population as with the FI or EI, the authors explained that the immigrant-only fractionalization measure will not be influenced by the single large group of native workers. Nevertheless, since AI accounts for the likelihood of meeting and interacting with those from other groups, estimates using this measure include the share of foreign-born workers in the total number as a control.

4. IMMIGRATION, BIRTHPLACE DIVERSITY AND PRODUCTIVITY: THE CASE OF SPAIN

Large-scale migration inflows are a relatively recent phenomenon in Spain. Indeed, until the last two decades of the previous century, this country was eminently a source of emigrants (Izquierdo, Jimeno and Lacuesta, 2015). At the beginning of the 20th century, Spain was behind the most developed European countries in terms of industrialization and urban development. Therefore, as explained by Bover and Velilla (1999), many Spanish emigrants moved to South American countries (Argentina, Brazil, Cuba, Uruguay) and North Africa (Algeria). Separate mention should be made of the large increase in emigration because of the Spanish Civil War (1936-1939), when over 500,000 people left the country. The main destinations were France, Mexico, Argentina and the USSR (Ricket, 2014). Later, throughout the 1960s and 1970s, given the poor economic conditions in Spain and political restrictions, mass emigration to Europe took place (Bover and Velilla, 1999).

However, this trend changed dramatically from the early 1990s, and most remarkably after 1997 (Izquierdo, Jimeno and Lacuesta, 2015). In just a few decades, Spain shifted from being a sending country to a receiving country in terms of migration, becoming an important recipient country for immigrants from countries in Africa, Asia, Latin America and Eastern Europe (González-López *et al.*, 2010). As can be seen in Figure 1, in 1998 the foreign population represented only 1.6% of the total population, while by 2016 this percentage had risen to almost 10%. The percentage of immigrants in the total population reached a peak of 12.2% during the years 2010 and 2011, even after the beginning of the global crisis in 2008.

Figure 1. Immigrant population in Spain over the total population 1998-2016.



Source: Developed by author based on INE data.

In the early years of the twentieth century, and motivated by economic expansion, immigration was mainly of an unskilled type, working in sectors such as agriculture, fishing, mining, manufacturing, hospitality and commerce doing jobs for which practically no skills or qualifications were needed. During the expansion, immigrants – mostly Europeans, closely followed by Latin Americans and Africans (Moroccans) – moved to Spain in search of more and better employment opportunities without drawing any kind of distinction between the types of position they could be employed in (Izquierdo, Jimeno and Lacuesta, 2015; Alamá-Sabater, Alguacil and Bernat-Martí, 2017). The beginning of the crisis also led to a sudden shift in this trend. In 2008 and 2009 the entries from South America started to decline and the rise in the number of European entries ceased (see Figure 1) [2].

Regarding the diversity and birthplace of the new residents, we can distinguish two types of immigrants: those from more developed countries and those from less developed economies. As mentioned before, in recent years there has been a change in terms of the origin and nature of immigrants. In 1998 most of the immigrants in Spain came from countries like Morocco, England, Germany, Portugal and France. After 2000, the arrival of immigrants from Latin America increased, especially those from Colombia, Ecuador and Bolivia. Moreover, despite its low importance until the end of the 20th century, as of 2008, the presence of Asians, especially those from China, increased notably (Delle Femmine and Alameda, 2017). As can be seen in Table 2, on the one hand, between 2008 and 2016 the presence of citizens from North and Central America and the Caribbean increased. On the other hand, the percentage of immigrants from South America, Africa and Asia decreased. Finally, there has been no excessively significant change in the percentage of immigrants from Europe arriving in Spain[3].

Table 2. Percentage of immigrants who arrived in Spain from each country in 2008 and 2016 over the total number of immigrants.

	2008	**2016**
Europe	**1.50%**	**1.49%**
North America	**0.51%**	**1.68%**
Central America-Caribe	**0.66%**	**1.74%**
South America	**2.49%**	**1.93%**
Asia	**1.37%**	**1.16%**
África	**1.78%**	**1.06%**

Source: Developed by the author based on INE data.

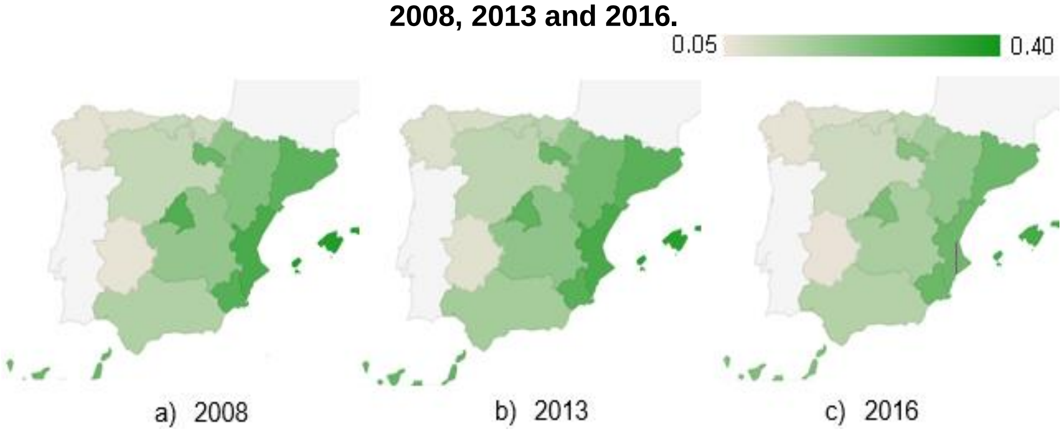
[2] See Annex 1 for more detailed information.
[3] See Annex 2 for more detailed information.

As indicated previously, nowadays, about 10% of the population of Spain are immigrants. According to Alamá-Sabater, Alguacil and Bernat-Martí (2017), during the first decade of the 21st century, when the Spanish economic “boom” took place, this country experienced one of the largest waves of migration in Europe. However, not all the population of foreign origin was distributed homogeneously.

During the years before the economic crisis, the vast majority of migrants in Spain were young and came from less developed countries, probably motivated by the hope of finding a new or better job. They therefore tended to choose regions with greater economic activity as their destination, and thus they were distributed in cities along the Mediterranean coast in the central and northern regions with higher employment rates and immigrant incomes (Alamá-Sabater, Alguacil and Bernat-Martí, 2017). In contrast, after the financial crisis, the number of the new residents in Spain rapidly decreased and the decision to locate in Spanish provinces seemed to be determined more by non-economic factors, such as good weather or a better lifestyle. In consequence, there was a greater presence of immigrants from countries with a high Human Development Index (HDI) located in the coastal regions (Alamá-Sabater, Alguacil and Bernat-Martí, 2017). Nevertheless, in some AC, such as Andalusia, the migration of non-skilled labourers to work in agricultural areas still predominates.

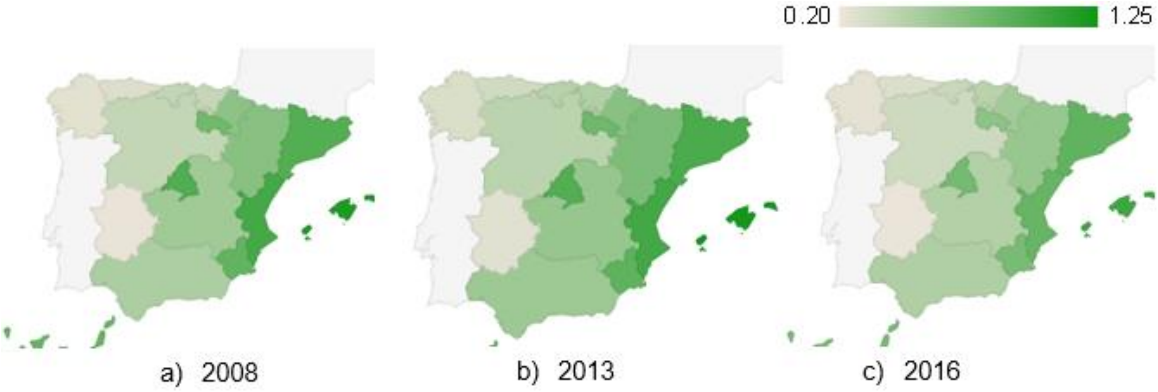
Similarly, when we analyse the birthplace diversity of immigrants across regions, we observe that the regions with the highest diversity of immigrants are the same throughout the period analysed, especially between 2008 and 2013. In 2016, we see that these regions continue to be the ones with high diversity, although it is lower. This decrease may be a consequence of the reduction in the number of immigrants in that year. In Figures 2, 3 and 4 we present the diversity of immigration across regions for the three different indexes, Fractionalization Index (FI), Entropy Index (EI) and Alesina Index (AI),

Figure 2. Maps of the Fractionalization Index by Autonomous Community in 2008, 2013 and 2016.



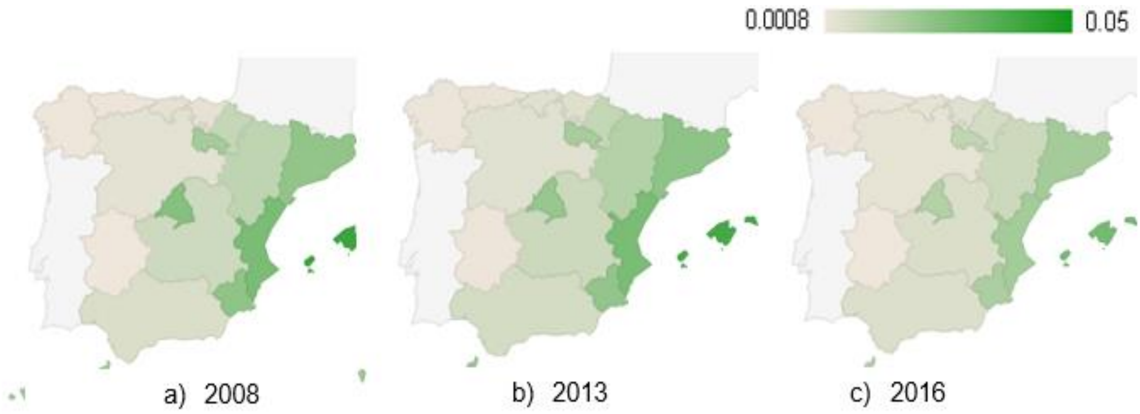
Source: Developed by the author based on INE data.

Figure 3. Maps of the Entropy Index by Autonomous Community in 2008, 2013 and 2016.



Source: Developed by author based on INE data.

Figure 4. Maps of the Alesina Index by Autonomous Community in 2008, 2013 and 2016.



Source: Developed by author based on INE data.

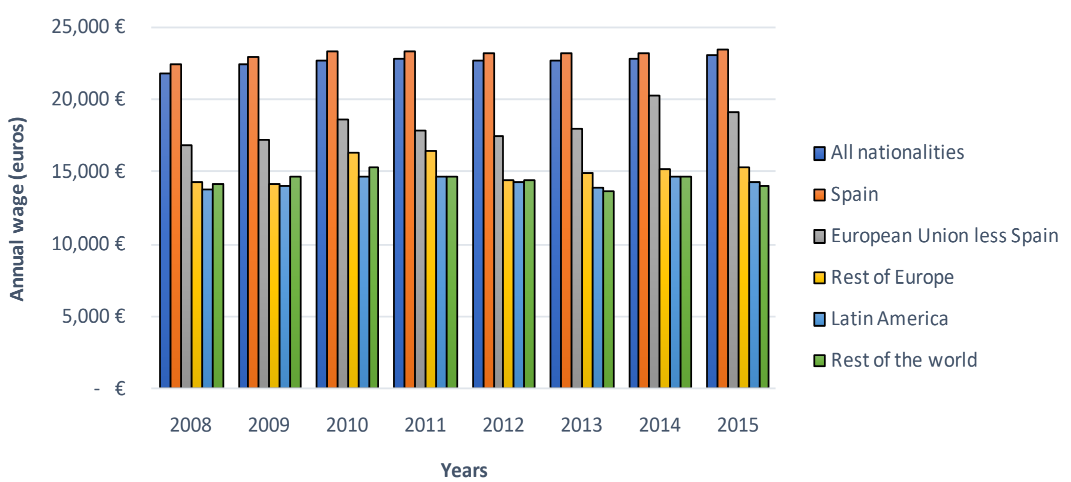
As the figures show[4], there is a wider range of immigrants in Barcelona and Madrid. According to Otero (2010), this is because these cities are important financial and business centres in Europe. Moreover, due to the large supply of the tertiary sector in these cities, the presence of Ibero-Americans and Africans is also quite significant. If we focus on the Valencian Community and Andalusia, we observe that both regions also have high diversity indexes. There is an important presence of foreigners from the European Union in the two regions. One of the reasons that leads a variety of citizens to migrate to these regions is the good weather and the tourist facilities. In the case of Andalusia, there is also a strong presence of individuals from Africa, especially those with low qualifications, who seek jobs in intensive agriculture. Ibero-Americans are concentrated in Alicante and those from non-EU Europe are more common in Castellón

[4] See Annexes 4, 5 and 6 for more detailed information.

and Valencia (both of them in the Valencian Community). In these regions, the Romanian population is particularly relevant. They mostly arrived before the crisis in search of job opportunities in the construction and tourism sectors. The high diversity of immigrants found in the Balearic and Canary Islands is probably due to the large supply of work found in the services sector, given the great importance that the tourism sector has in both cases. In coastal regions and the capital city, Madrid, we observe the presence of a higher number of nationalities, while in regions like Extremadura, Asturias or Navarra there seems to be less diversity.

The goal of this paper is to analyse how a higher degree of diversity in migration influences workers' productivity across regions. As the economic literature has highlighted, several factors determine the level of productivity of a region. According to Aguayo and Guisán (2008), examples of such factors would be physical capital per worker (machinery and production facilities), human capital (higher qualification of workers in terms of both direct production of companies and the production of complementary goods and services carried out by other companies) and greater social capital (which includes elements of social trust, political trust and other positive elements that generate a social environment to support productive initiatives and cooperation). In this study, we use real wage per capita as a proxy of worker productivity. As we can see in Figure 5, there are important differences in wages between Spaniards and non-nationals[5]. The native population has the highest wages, followed by European citizens, since migrant flows of skilled workers usually predominate among European countries (Mahroum, 2001). Among non-nationals, those from Latin America seem to be among the worst paid.

Figure 5. Average annual wage in Spain by nationalities.

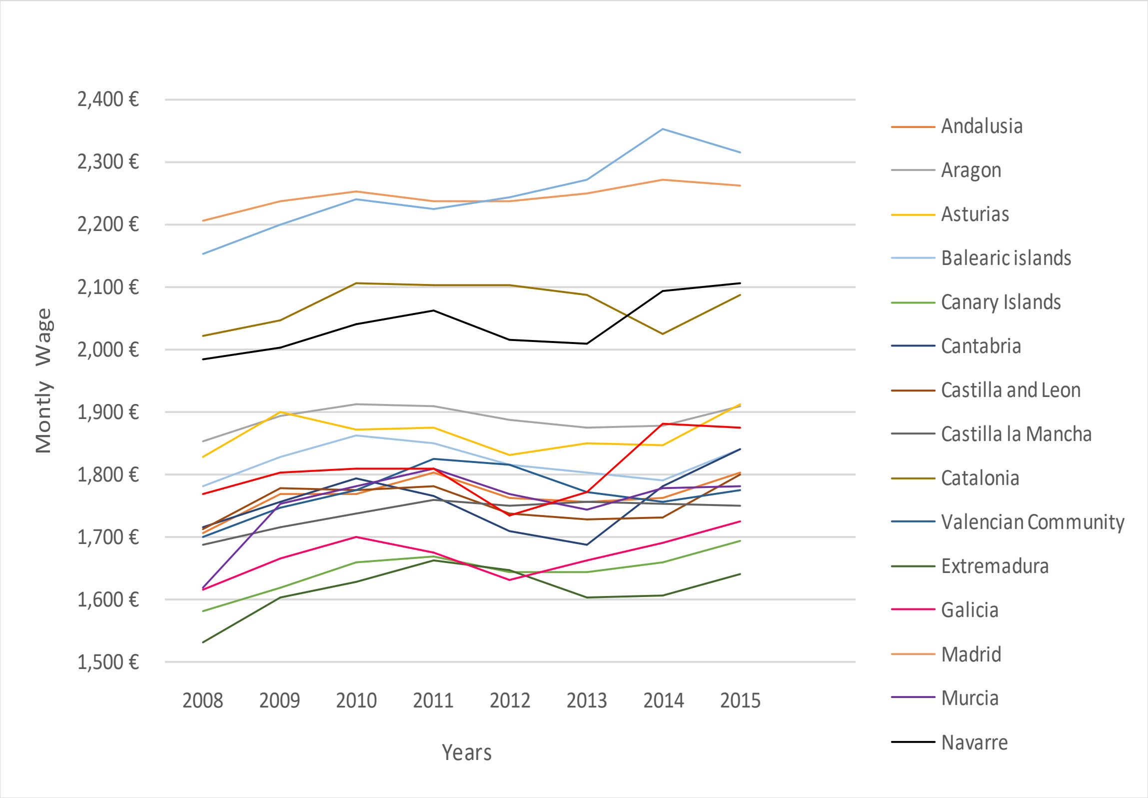


Source: Developed by author based on INE data.

[5] See Annex 7 for further information.

However, considering the average wage cost of the entire population, we observe that it changes significantly across regions and over time[6] (see Figure 6). Throughout all the sample period, wages are higher in the Basque Country, Navarre, Madrid and Catalonia. These last two regions coincide with those with the highest index of immigrant diversity (see Figures 2, 3 and 4). In addition, regions with low wages are those in which the supply of unskilled labour is higher due to the relevance of agriculture. Accordingly, we find lower wages in Extremadura, Galicia, Castilla and León, Castilla La Mancha and Andalusia, regions with high agricultural and livestock activity.

Figure 6. Monthly wage cost by Autonomous Communities



The foregoing stylized facts reveal that that there has not only been a change in the migration inflows of Spain, by which it has gone from being a sending country to a receiving country, but also a qualitative change in terms of the diversity of the new residents. In general, as the descriptive evidence shows, those regions where we find higher wages per capita are also those with a greater presence of different nationalities. This positive relationship between productivity and birthplace diversity in Spain is also confirmed by the upward slopes shown in Figure 7, where the log of wage is represented with respect to the different diversity indexes.

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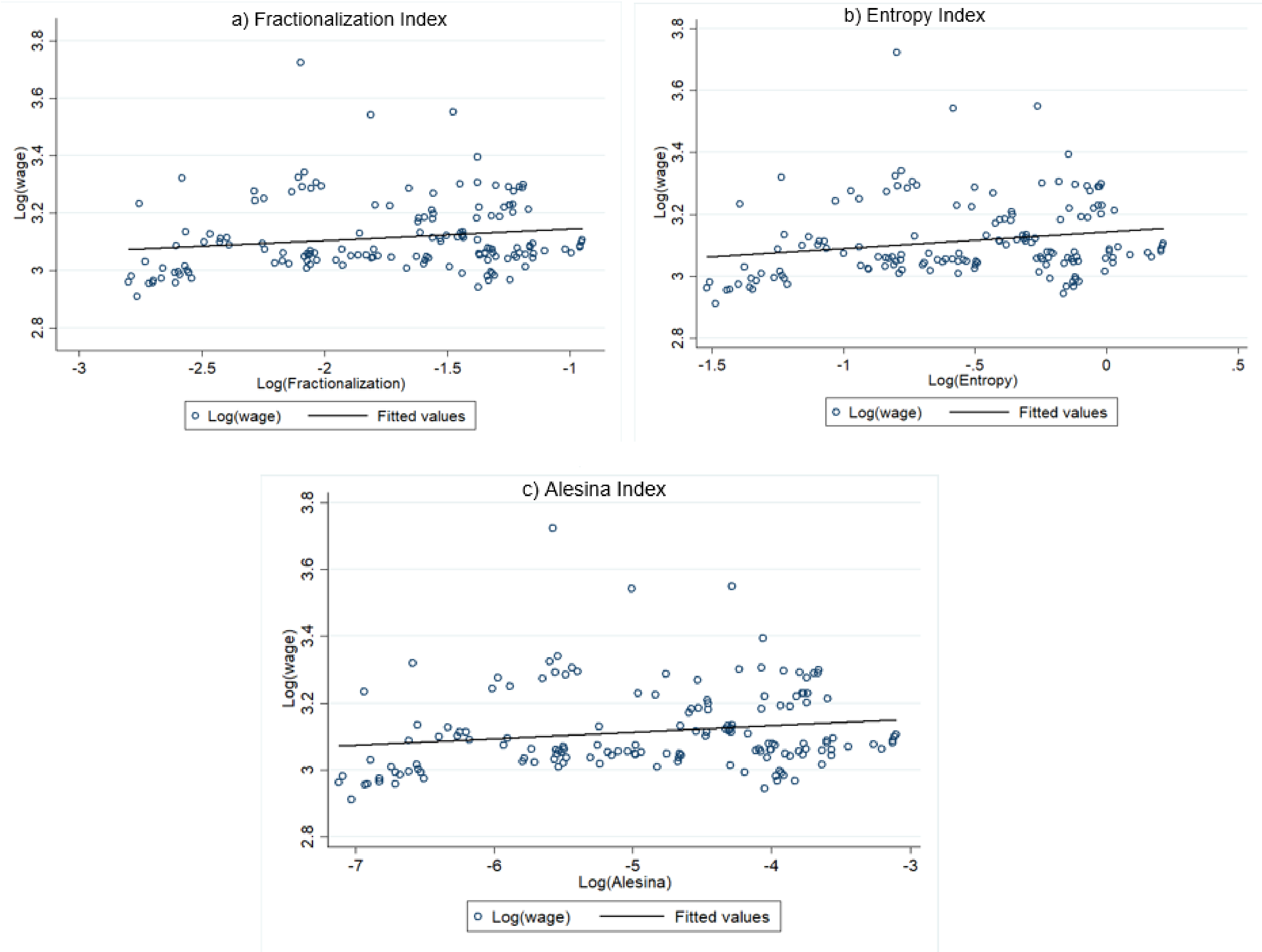
6 See Annex 8 for more information.

Figure 7. Relationship between birthplace diversity and productivity.



Source: Developed by author based on INE data.

5. DATA AND ECONOMETRIC MODEL

5.1 Data and Variables

In order to analyse the effect that the diversity of immigration has on workers' productivity in Spain, we used information from the 17 Spanish AC covering the period 2008 and 2016. The sample period was selected with the purpose of evaluating the connections between immigrants' diversity and productivity both during the crisis and afterwards.

Generally, the analysis of the existence of spillovers from immigrant diversity is not an easy task given the restrictions in terms of data availability. In our case, we built a database using data from both the Spanish National Institute of Statistics (INE) and the EDUCAbase (from the Ministry of Education, Culture and Sports), which has allowed us

Table 3. Definition and data sources

Variable	Description	Data Source
Wage	Log of the average annual gross salary per Autonomous Community	Active Population Survey available in the INE
Fractionalization	Log of a birthplace index based on Kemeny and Cooke (2017)	Author's calculations based on Statistics National Institute
Entropy	Log of a birthplace index based on Kemeny and Cooke (2017)	Author's calculations based on Statistics National Institute
Alesina	Log of a birthplace index based on Kemeny and Cooke (2017)	Author's calculations based on Statistics National Institute
Population	Log of total population by autonomous community	Statistics of the Continuous Register available in the INE
Young Population	Log of the share of young population, considering as young population those aged between 15 and 29 years	Statistics of the Continuous Register available in the INE
High Education	Log of the share of population that has superior studies to the 2nd stage of Secondary Education	EDUCAbase database from the Ministry of Education, Culture and Sports
Natives Unemployment	Log of the unemployment rate of the native population by Autonomous Community	Active Population Survey available in the INE
ShareHDI	Log of the share of immigrants arrived in each Autonomous Community that come from countries with a high or very high level of human development.	Migration Statistics available in Statistics National Institute and Human Development Reports of the United Nations Development Program
'Predicted' change in the number of immigrants	Log of a birthplace index based on Ottaviano and Peri (2006)	Author's calculations based on Statistics National Institute

Source: Developed by author based on INE data.

to carry out the study at a NUTS 2 level. Table 3 contains a detailed explanation and the source of the variables used.

Following previous literature, productivity has been proxied here by national real wages. Other authors, such Kemeny and Cooke (2018) and Ottaviano and Peri (2006), have also used this variable as an approximation of worker productivity. Particularly, we employ the average annual gross wage per AC. Alternatively, as a robustness test, we have measured productivity as the real wages of the total population, that is, considering both immigrants and nationals[7].

As our main regressor, the diversity of migration has been computed here by three different indexes: Fractionalization Index, Entropy Index and Alesina Index, which have been calculated as explained earlier in Section 3. Consistent with previously literature, several characteristics of the region were considered as additional control variables. As in Ottaviano and Peri (2006), here we include total population to capture the scale of the region. Moreover, following Gagliardi (2015), the proportion of young population has been included as an additional regressor. According to the United Nations (2015), young people are a positive force for productivity when they are provided with the knowledge and opportunities necessary to thrive, because they have skills acquired during their education that allow them to contribute to economic productivity.

Following Gagliardi (2015), additionally we introduce the unemployment rate of the natives to capture the employment opportunities offered by each region. The weight of this variable is especially relevant for the so-called labour immigrants.

Finally, given the relevance that human capital has on productivity, as initially highlighted in the seminal paper by Lucas (1988), in this work we have included this variable considering both national human capital and imported human capital. The first has been proxied by the share of population that has reached high educational levels[8]. This variable has also been used Bove and Elia (2017) and Alesina *et al.* (2013). Similarly,

[7] Given the lack of data for 2016, wages for that year have been calculated applying a growth rate similar to that experienced by the data for the national real wages in previous years.

[8] For the coding of the variable "high education" in the EPA, until 2013 the National Classification of Education 2000 (CNED-2000) was applied, which is compatible with the International Standard Classification of Education 1997 (ISCED-97). As of 2014, a series rupture when the new National Classification of Education 2014 was applied (CNED-2014), compatible with the International Standard Classification of Education 2011 (ISCED-2011). Source: Ministry of Education, Culture and Sports.

The information is found in EDUCAbase, a database provided by the Spanish Ministry of Education, Culture and Sports that collects the data from the Exploitation of the educational variables of the Labour Force Survey offered by the INE. This survey represents a synthesis of information based on the educational variables of the Labour Force Survey and the Community Labour Force Survey.

Saks *et al.* (2015) found a robust positive relation between higher education and an increase in productivity and wages. Nonetheless, as mentioned by Nathan (2015), this higher human capital may also be due to the entrance of skilled migration. According to this author, the arrival of skilled people has a significant and positive impact on the labour market of the destination countries. In our work, this variable has been proxied by the percentage of immigrants that arrived from countries with high or very high levels of HDI as a proxy of skilled immigrants.

In Table 4 and 5, we present the main statistics and correlation matrix of these variables, respectively.

Table 4. Main statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Wage	153	22.72	3.174	18.35	41.40
Fractionalization	153	0.196	0.0881	0.0609	0.387
Entropy	153	0.646	0.268	0.218	1.241
Alesina	153	0.0123	0.0105	0.000809	0.0449
Population	153	2.745	2.451	0.316	8.450
Young Population	153	0.0467	0.00587	0.0348	0.0616
High Education	153	0.236	0.0544	0.151	0.486
Natives unemployment	153	17.88	6.883	5.388	35.74
ShareHDI	153	0.715	0.0882	0.492	0.862
Predicted Diversity	136	0.000397	0.546	0.00001	0.00011

Source: Developed by author.

Table 5. Correlation matrix

	Wage	Population	Young Population	High Education	Natives unemployment	ShareHDI
Wage	1.000					
Population	0.147	1.000				
Young Population	-0.357	0.1785	1.000			
High Education	0.666	-0.075	-0.307	1.000		
Natives unemployment	-0.384	0.283	0.297	-0.216	1.000	
ShareHDI	-0.416	0.04	-0.100	0.619	0.124	1.000

Source: Own elaboration

Source: Developed by author.

As can be appreciated from Table 5, we obtain a high positive correlation between higher education and the share of immigrants coming from countries with high HDI indicating that those regions with more skilled workers are also the ones that attract immigrants from more developed countries.

5.2 Estimation methodology

For the estimation of the productivity spillovers of birthplace diversity, we employed the panel data methodology. This allowed us to account for both time effects and unobserved individual heterogeneity. As previously mentioned, to do so, we used data from the 17 Spanish AC during the period between 2008 and 2016.

Following the recent literature, we analysed how the aggregate birthplace diversity influences worker productivity, after controlling for other regional factors such as total population, young population, share of population with higher education, natives' unemployment and the share of immigrants arriving in each AC from countries with a high or very high level of human development. More specifically, the estimated equation takes the following form:

$$\begin{aligned} &ln\left(wage_{c,t}\right) \\ &= \beta_0 + \beta_1 \;\; ln\left(birthplace\_index_{c,t}\right)^k + \\ &+ \beta_2 \;\; ln(popul_{c,t}) + \beta_3 ln(youngpop_{c,t}) + \beta_4 ln(higheduc_{c,t}) \\ &+ \beta_5 ln(unemnat_{c,t}) + \beta_6 ln(shareHDI_{c,t}) + \varepsilon_c + \varepsilon_t + \varepsilon_{c,t} \end{aligned} \tag{4}$$

where *c* stands for each Autonomous Community and *t* denotes time, specifically, each year analysed; $wage_{c,t}$ indicates the average real wage of the national population of each region; $birthplace\_index_{c,t}$ represents the different indexes we have used to measure diversity; where $k \in [1,3]$ indicates each of the three indexes calculated; $popul_{c,t}$ and $youngpop_{c,t}$ indicate the population and young population enumerated in each region; $higheduc_{c,t}$ shows us what percentage of the total population has higher education, ; $unemnat_{c,t}$ constitutes the unemployment rate of the natives; and finally $shareHDI_{c,t}$ allows us to control for what part of the foreigners come from countries with high and very high HDI. All these variables are expressed in natural logarithms. Thus, the coefficients that accompany the explanatory variables will indicate the elasticity of the dependent variable with respect to the independent variables, that is, the percentage change in the dependent variable for a percentage change given in the regressor.

Let ε_c represent time-invariant permanent differences across AC, and let ε_t be the time effects that affect the regions identically in each period. Finally, $\varepsilon_{c,t}$ is the random error term with a mean of zero, which is assumed to be independent across countries and over time.

The decision as to whether to consider unobserved country-specific effects as fixed or random is made based on the Hausman test. Fixed effects allow for unobservable factors, i.e. omitted variables that can be correlated with the explanatory variables, which vary between the individual entities and do not change over time, whereas random effects indicate that the exact value at the origin that each individual may have is not sure, but it is considered that it will probably gravitate around a central value. Hausman illustrated that the difference between the coefficients of fixed and random effects $(\beta_{fe} - \beta_{re})$ might be used to prove the null hypothesis that the random error term and the explanatory variables are not correlated. Thus, the H_0 of the Hausman test is that the estimators of random effects and fixed effects do not differ substantially. If the H_0 is rejected, the estimators differ, and the conclusion is that fixed effects are more convenient than random effects. If H_0 cannot be rejected, it will be preferable to use random effects because, although the two methods would be consistent, when using random effects, the model will be more efficient[9].

Moreover, an autocorrelation test proposed by Wooldridge (2002)[10] was used to test autocorrelation problems in the models. The null hypothesis of this test is that there is no autocorrelation; if it is rejected, it can be concluded that it exists. Robust standard errors are calculated to eliminate potential heteroscedasticity and autocorrelation of the panel data.

For comparative purposes and to address the problem of both endogeneity and reverse causality, we estimated the coefficient of the model using the two-stage least squares (2SLS) methodology. The plausibility of both the potential positive impact of an increase in the migration diversity on productivity and the possibility of regions with a higher productivity attracting immigrants from a greater number of countries has been

[9] From modern econometrics it is known that if the individual effects are correlated with the other regressors in the model, the fixed effect model is consistent, and the random effects model is inconsistent. Conversely, if the individual effects are not correlated with the other regressors in the model, as established under the null hypothesis in the Hausman test, both random and fixed effects are consistent and random effects are efficient. See Greene (2012) for more details.

[10] The Wooldridge method uses the residuals of a regression of first differences, observing that if u_{it} is not serially correlated, then the correlation between the differentiated u_{it} errors for period t and t-1 is equal to -0.5. In fact, the Wooldridge test is designed to prove this equality. For a more extensive discussion of this test, see Wooldridge, J.M. 2002. Econometric Analysis of Cross Section and Panel Data. Cambridge, MA: MIT Press.

documented in the literature (Ottaviano and Peri, 2006). As authors like Kemeny and Cooke (2018) have explained, more productive regions can also be the ones that attract a wider range of immigrants of different nationalities. That is, regions may experience an increase in the average wage of a positive economic shock, which attracts immigrants disproportionately and therefore witnesses an increase in diversity. If these two bidirectional causalities occur, the measured impact of diversity on wages and incomes would be biased upwards (Ottaviano and Peri, 2006). This makes it necessary to consider the likelihood of a reverse causality in our analysis.

6. MAIN RESULTS

6.1 Fixed effects estimation

Table 6 presents the estimates of Eq. 4 using the fixed effects (FE) estimation methodology. As can be seen at the bottom of this table, the Hausman test statistic suggests that in all cases the fixed effects model is preferred to the random effects model. In addition, from the Wooldridge test for autocorrelation, we can conclude that the data do not have first-order autocorrelation.

Table 6. Estimation results of Wage using Fixed Effects estimation: 2008-2016.

	(1)	(2)	(3)
	Fractionalization	**Entropy**	**Alesina**
Fractionalization	0.149*		
	(0.0879)		
Entropy		0.196**	
		(0.0971)	
Alesina			0.0813**
			(0.0407)
Population	-0.0352	-0.0430	-0.0284
	(0.354)	(0.351)	(0.352)
Young Population	0.803***	0.813***	0.816***
	(0.124)	(0.122)	(0.123)
High Education	0.302***	0.301***	0.299***
	(0.0391)	(0.0388)	(0.0390)
Natives Unemployment	-0.0685	-0.0657	-0.0687
	(0.0461)	(0.0460)	(0.0458)
ShareHDI	0.380**	0.397***	0.398***
	(0.150)	(0.147)	(0.148)
Constant	6.493***	6.370***	6.666***
	(0.568)	(0.527)	(0.590)
Observations	153	153	153
R-squared	0.848	0.849	0.849
Number of Autonomous Communities	17	17	17
Autonomous Community FE	YES	YES	YES
Year FE	YES	YES	YES
Hausman Test	31.68	33.85	33.76
	(0.0045)	(0.0022)	(0.0022)
Wooldridge test for autocorrelation	2.451	2.417	2.369
	(0.1370)	(0.1396)	(0.1433)

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. For the Hausmann test and the Wooldridge test for autocorrelation, we report the p-values in parentheses.

The coefficients in Table 6 are shown sequentially for the three alternative measures of migration diversity (FI, EI and AI, respectively). The first observation in this table is the significance of the birthplace diversity index in all regressions, this result being consistent with our main hypothesis of the existence of a positive productivity spillover from greater immigration diversity. Specifically, the estimated coefficients imply that, on average, an increase in the FI of 10 percentage points leads to a rise in national wage of 1.49 percentage points, keeping the other factors constant. A higher impact is seen with the EI, as an increase by 10 percentage points will predict a growth in national wages of 1.96 percentage points, ceteris paribus. However, this effect is significantly smaller when we consider the AI. In this case, a higher index, around 10 percentage points, implies an increase of 0.8 percentage points in wages. The smaller value of this last index may be explained by the very nature of the Alesina Index. As shown previously, this index calculates the diversity strictly among those born abroad in a given place, instead of capturing heterogeneity among all individuals.

Coefficients on other control variables show the expected signs. Moreover, we find that, except for population and unemployment, all of them seem to have a significant effect on productivity. The lack of significance of population may be due to the inclusion of other variables, such as a young population, that may capture in some way the scale of the region (even when the correlation between these two variables, although positive, is not significantly high). As can be seen in Table 6, the results from all the regressions suggest a positive and significant influence of a greater proportion of young population in productivity. Specifically, an increase of 10 percentage points in the rate of young population in each AC increases the average wage for nationals above 8 percentage points, other factors being equal. Similarly, our estimates verify the beneficial impact of skilled labour on productivity. In particular, an increase of 10 percentage points in the percentage of the population with higher education will result in a rise in wages by 3 percentage points. The presence of migrants arriving from countries with a high or very high HDI also appears to be positively correlated with national wages. According to our estimates, with a share of 10 points higher, productivity will increase by approximately 4 percentage points. In contrast, the unemployment rate for natives seems to have a negative influence on national wages.

As a robustness check, we re-estimated the previous model using the total wage of the population as a dependent variable, considering the earnings from both immigrants and nationals. Accordingly, the estimated equation now takes the following form:

$$\ln(wagetot_{c,t}) = \beta_0 + \beta_1 \ ln(birthplace\_index_{c,t})^k + + \beta_2 \ ln(popul_{c,t}) + \beta_3 ln(youngpop_{c,t}) + \beta_4 ln(higheduc_{c,t}) + \beta_5 ln(unemnat_{c,t}) + \beta_6 ln(shareHDI_{c,t}) + \varepsilon_c + \varepsilon_t + \varepsilon_{c,t} \quad (5)$$

where $wagetot_{c,t}$ represents the real wage of the total population and the subscripts and the rest of the variables have the same definition as previously in Eq. 4.

Following the results of the Hausman test, the coefficients have been estimated once again through the FE methodology. The estimates are presented in Table 7.

Table 7. Estimation results of Total Wage using Fixed Effects estimation: 2008-2016.

	(1) Fractionalization	(2) Entropy	(3) Alesina
Fractionalization	0.134		
	(0.0879)		
Entropy		0.182*	
		(0.0971)	
Alesina			0.0733*
			(0.0408)
Population	0.0733	0.0673	0.0796
	(0.354)	(0.352)	(0.352)
Young Population	0.842***	0.854***	0.855***
	(0.124)	(0.123)	(0.123)
High Education	0.284***	0.282***	0.281***
	(0.0391)	(0.0389)	(0.0391)
Natives Unemployment	-0.0800*	-0.0771*	-0.0802*
	(0.0462)	(0.0460)	(0.0458)
ShareHDI	0.420***	0.441***	0.437***
	(0.150)	(0.147)	(0.148)
Constant	6.505***	6.404***	6.662***
	(0.569)	(0.527)	(0.591)
Observations	153	153	153
R-squared	0.848	0.849	0.849
Number of Autonomous Communities	17	17	17
Autonomous Community FE	YES	YES	YES
Year FE	YES	YES	YES
Hausman Test	33.03	35.58	35.30
	(0.0029)	(0.0012)	(0.0008)
Wooldridge test for autocorrelation	1.306	1.301	1.275
	(0.2698)	(0.2709)	(0.2756)

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. For the Hausmann test and the Wooldridge test for autocorrelation, we report the p-values in parentheses.

In general, the estimates obtained in these regressions confirm our previous outcomes, although now only two of the three diversity indexes (EI and AI) are significant. The lack of significance of the FI might be explained by the possibility that the FI is biased because of the presence of a large proportion of immigrants in a region, even when these immigrants do not come from a wide range of countries of origin. Note, however, that the value and sign of the coefficient on both indexes, EI and AI, are similar to those previously estimated. An increase in the FI and in the EI of 10 percentage points will lead to an increase in the average wage of the total population by 1.34 and 1.82 percentage points respectively, whereas the same increase in the AI will imply a rise in the wage by 0.73 percentage points (other things being equal).

The estimates for the other control variables confirm the beneficial influence that a greater young and skilled population has on productivity; as well as the positive productivity spillover of an increase in immigration from countries with a high or very high HDI. The three regressions predict that an increase of 10 percentage points in the young population of each AC increases the total wage by approximately 8 percentage points. Similarly, an increase of 10 percentage points in the rate of population with higher education will increase total wages by 3 percentage points. Finally, in the case of an increase of 10 percentage points in the share of immigrants who arrived in each AC from countries with a high or very high level of HDI will increase productivity by approximately 4 percentage points. Regarding the unemployment rate of natives, the estimated coefficients indicate a decrease of approximately 0.8 percentage points in total wages due to a rise of 10 percentage points in the unemployment rate. Finally, as can be seen at the bottom of the table, in all cases the Wooldridge test for autocorrelation shows us that data do not have first-order autocorrelation.

6.2 Endogeneity and instrumental variable (IV) approach

As mentioned above, the FE estimation takes into account unobserved heterogeneity among regions. However, it does not consider a potential simultaneity problem or reverse causality. Nonetheless, as pointed out by Cadena *et al.* (2013) and Lewis and Peri (2014), among others, the location of immigrants is not a random selection. In contrast, this may depend on the local economic outcomes. Consequently, whenever the amount of diversity of immigrants in a region and its economic performance are interrelated, we need to be cautious in our estimations in order to avoid upward biased estimates. To overcome this, we employ Two-Stage Least Squares (2SLS) by using an instrumental variable whose exogenous variation affects migration diversity in a region, but not the total worker productivity. Thus, this variable allows us to isolate that portion of the correlation between diversity and wages that is due to the causal effect of diversity in wages (Ottaviano and Peri, 2006).

The instrument used in our regressions is a type of diversity index that was initially proposed by Ottaviano and Peri (2006), which later became a standard instrument in literature, as in the case of Gagliardi (2015). According to Ottaviano and Peri (2006), immigrants tend to settle, at least initially, where other immigrants from the same country already reside. In consequence, this index is constructed as the “predicted” change in the number of immigrants from each country in each Autonomous Community during the period 2008-2016. By construction, the predicted change does not depend on any specific Autonomous Community economic shock during the observed period.

First, the growth rate of immigration is calculated for each group of immigrants according to their birthplace[11]. Thus, using the same notation as in the previous indexes, we have:

$$(g_r)_{y1-y2} = \frac{\left(s_{rj}\right)_{y2} - \left(s_{rj}\right)_{y1}}{\left(s_{rj}\right)_{y1}} \tag{6}$$

whereg_r is the growth rate of immigrants born in country *r, y1* represents year 1 and *y2* represents year 2.

Second, from the above equation, we calculate the "attributed" share of people born in country j and residing in autonomous community c in year 2:

$$\left(\widehat{s_{rj}^{c}}\right)_{y2} = \left(g_{rj}^{c}\right)_{y2} \cdot \left[1 + (g_r)_{y1-y2}\right] \tag{7}$$

As a final stage, we obtain a diversity index, *div*, through the attributed share of foreign-born individuals:

$$\widehat{div}_{c,y2} = 1 - \sum_i \left(\widehat{s_{rj}^{c}}\right)_{y2}^{\;2} \tag{8}$$

As Ottaviano and Peri (2006) explained, the variable *div* is independent of any specific shock in an AC during the period, since the attributed diversity for each Autonomous Community in year 2 is built using the participation of the autonomous community in year 1 and the national growth rates of $y1 - y2$ of each group of immigrants[12].

[11] It will be calculated from year to year since 2009, since as it does not have information for 2007, the first available growth rate will be that of 2009, to 2016.
[12] Consequently, 17 observations corresponding to the year 2008 have been lost.

Table 8. Estimation results of Wu-Hausman endogeneity test

	(1) Fractionalization	(2) Entropy	(3) Alesina
Residuals1	-0.217**		
	(0.0908)		
Residuals2		-0.202**	
		(0.0847)	
Residuals3			-0.0942**
			(0.0398)
Fractionalization	0.126		
	(0.0830)		
Entropy		0.106	
		(0.0760)	
Alesina			0.0533
			(0.0361)
Population	0.0337*	0.0345*	0.0343*
	(0.0195)	(0.0199)	(0.0196)
Young Population	-0.200	-0.0457	-0.127
	(0.267)	(0.207)	(0.240)
High Education	-0.0504	0.0298	-0.0104
	(0.183)	(0.150)	(0.168)
Natives Unemployment	-0.155***	-0.175***	-0.164***
	(0.0512)	(0.0471)	(0.0492)
ShareHDI	-0.0707	-0.0685	-0.0698
	(0.101)	(0.102)	(0.102)
Constant	2.988***	3.466***	3.329***
	-1.028	(0.868)	(0.892)
Observations	136	136	136
Number of CCAA	17	17	17

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Thus, this variable would meet the exogeneity requirements needed for a good instrument.

In order to check whether or not the diversity indexes used as explanatory variables in our productivity regressions are endogenous, we ran the Wu-Hausman endogeneity test. This test allowed us to determine whether the covariance between the indexes used as independent variables and the error term $\varepsilon_{c,t}$ was equal to zero. To compute this test, we used the residuals from the regression of the endogenous variable and included them as additional regressors in the original OLS equation. Under the null hypothesis of no endogeneity, OLS is consistent and efficient, while IV is also consistent, but inefficient. If endogeneity exists, an IV estimation methodology is required to guarantee consistent estimations.

As can be observed in Table 8, the residuals[13] are significant in all regressions, which indicates that the null hypothesis of non-endogeneity must be rejected. So, we can conclude that these diversity indexes are endogenous. Therefore, ignoring this fact could lead to inconsistent estimates and biased conclusions.

To deal with the problem of endogeneity, we estimated our model using IV techniques. Accordingly, an exogenous variable must be proposed to act as an instrument of the endogenous variables. As is well known, two criteria are necessary for an instrument to be valid: relevance and exogeneity. The relevance criteria are properly tested in Table 9. As can be seen in this table, the instrumental variable (*div*) is significant to explain the endogenous variable in the three cases. Consequently, the relevance condition is fulfilled, so it can be considered an adequate instrumental variable for the analysis.

Table 9. Estimation results of relevance condition

Dependent variables	(1) Fractionalization	(2) Entropy	(3) Alesina
Predicted Diversity	0.0725***	0.0772***	0.170***
	(0.0237)	(0.0210)	(0.0512)
Population	0.872**	0.823**	1.761**
	(0.372)	(0.330)	(0.804)
Young Population	-0.501***	-0.451***	-1.117***
	(0.111)	(0.0988)	(0.241)
High Education	0.0581*	0.0434	0.127*
	(0.0349)	(0.0310)	(0.0754)
Natives Unemployment	-0.0174	-0.0169	-0.00496
	(0.0462)	(0.0409)	(0.0997)
ShareHDI	-0.747***	-0.607***	-1.526***
	(0.122)	(0.108)	(0.263)
Constant	-3.278***	-1.828***	-8.144***
	(0.488)	(0.433)	(1.054)
Observations	136	136	136
R-squared	0.929	0.928	0.930
Number of CCAA	17	17	17
Autonomous Community FE	YES	YES	YES
Year FE	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[13] Residuals1 for fractionalization, Residuals2 for Entropy and Residuals3 for Alesina.

Next we present the estimations of the model obtained with the 2SLS methodology using the predicted change in the number of immigrants coming from each country as an IV (see Table 10).

As in the previous estimation, the three diversity indexes (FI, EI and AI) are now positive and statistically significant in the explanation of the average wage, suggesting that an increase in the diversity of immigrants is associated with higher productivity. In particular, similarly to the FE estimates, we find that when the FI rises by 10 percentage points, national wages go up 8.36 percentage points. In the regression of the EI, outcomes are similar with a coefficient of 7.86 percentage points. As in the FE regression, the effect that an increase in the AI has on productivity is lower than those obtained with the previous indexes, although higher than that achieved through the regression with fixed effects. A growth of 10 percentage points in the AI now leads to an increase in wages of 3.57 percentage points.

Table 10. Estimation results of wage using IV through 2SLS.

	(1) Fractionalization	(2) Entropy	(3) Alesina
Fractionalization	0.836*		
	(0.463)		
Entropy		0.786*	
		(0.410)	
Alesina			0.357*
			(0.190)
Population	-0.560	-0.478	-0.460
	(0.632)	(0.573)	(0.580)
Young Population	1.128***	1.062***	1.107***
	(0.252)	(0.212)	(0.234)
High Education	0.248***	0.263***	0.251***
	(0.0606)	(0.0529)	(0.0573)
National Unemployment	-0.0532	-0.0544	-0.0659
	(0.0659)	(0.0620)	(0.0629)
ShareHDI	0.943**	0.796**	0.863**
	(0.406)	(0.315)	(0.353)
Constant	9.097***	7.791***	9.264***
	(1.783)	(1.082)	(1.797)
Observations	136	136	136
Number of CCAA	17	17	17
Autonomous Community effect	YES	YES	YES
Time effect	YES	YES	YES
Instrumental Variables	YES	YES	YES

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11. Estimation results of Wu-Hausman endogeneity test (robustness).

	(1) Fractionalization	(2) Entropy	(3) Alesina
Residuals1	-0.230**		
	(0.0910)		
Residuals2		-0.216**	
		(0.0850)	
Residuals3			-0.100**
			(0.0399)
Fractionalization	0.122		
	(0.0832)		
Entropy		0.100	
		(0.0764)	
Alesina			0.0511
			(0.0363)
Population	0.0338*	0.0347*	0.0344*
	(0.0196)	(0.0202)	(0.0198)
Young Population	-0.195	-0.0351	-0.121
	(0.267)	(0.208)	(0.241)
High Education	-0.0923	-0.00999	-0.0520
	(0.183)	(0.150)	(0.168)
Natives Unemployment	-0.168***	-0.189***	-0.177***
	(0.0513)	(0.0473)	(0.0493)
ShareHDI	-0.0442	-0.0398	-0.0428
	(0.102)	(0.103)	(0.102)
Constant	2.953***	3.459***	3.295***
	(1.031)	(0.872)	(0.894)
Observations	136	136	136
Number of CCAA	17	17	17

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Besides, the results of the 2SLS regressions confirm the expected effect of the other control variables on productivity. Moreover, the results of the 2SLS regressions confirm the expected effect of the other control variables on productivity. A higher rate of young and educated population significantly influences productivity, leading to an increase in wages of approximately 11 and 2.3 percentage points in the three cases, respectively. Similarly, our estimates verify the productivity spillovers of a higher proportion of skilled immigrants. Particularly, according to our estimations, an increase of 10 percentage points in the share of immigrants that come from countries with a high or very high level of HDI will imply a growth in wages of around 8-9 percentage points. As in fixed effects regressions, the variable total population is not statistically significant. Moreover, the rate of unemployment of the native population does not seem to have any significant effect on productivity now.

Table 12. Estimation results of wage using IV through 2SLS (robustness).

	(1) Fractionalization	(2) Entropy	(3) Alesina
Fractionalization	0.889*		
	(0.472)		
Entropy		0.836**	
		(0.415)	
Alesina			0.380**
			(0.194)
Population	-0.524	-0.437	-0.418
	(0.644)	(0.580)	(0.590)
Young Population	1.199***	1.130***	1.177***
	(0.257)	(0.214)	(0.238)
High Education	0.226***	0.242***	0.230***
	(0.0618)	(0.0536)	(0.0584)
National Unemployment	-0.0675	-0.0688	-0.0810
	(0.0672)	(0.0628)	(0.0640)
ShareHDI	1.036**	0.879***	0.951***
	(0.414)	(0.319)	(0.359)
Constant	9.394***	8.006***	9.572***
	(1.818)	(1.096)	(1.830)
Observations	136	136	136
Number of CCAA	17	17	17
Autonomous Community effect	YES	YES	YES
Time effect	YES	YES	YES
Instrumental Variables	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Next, for robustness, we perform a similar analysis now considering the productivity of total workers (including non-native ones) as a dependent variable. First, the problem of a non-random selection in the location of immigrants is analysed through the Wu-Hausman endogeneity test. As can be seen in Table 11, the residuals[14] are significant in the three regressions, so the null hypothesis of non-endogeneity must be rejected. Therefore, we can conclude that these indexes are endogenous in the explanation of the total wages, which may lead to biased results for endogeneity. Accordingly, as before,

[14] Residuals1 for fractionalization, Residuals2 for Entropy and Residuals3 for Alesina.

we use the predicted change in the number of immigrants coming from each country as the instrumental variable in the 2SLS estimation.

The estimations shown in Table 12 confirm our previous conclusions. Again, the three diversity indexes are positive and statistically significant. Furthermore, the roles of the other control variables in the explanation of total wages are similar to those obtained previously.

To sum up, our estimates consistently confirm a positive and largely significant relationship between regional immigrant diversity and worker productivity (for total and nationals). Moreover, these outcomes are robust to both the unobserved regional heterogeneity and to the presence of a possible interconnection between the economic effects of a greater diversity of immigrants and the relevance that the economic conditions may exert on the attraction of a more diverse range of non-residents. Finally, we verify the important role of an increase in young and trained workforce to encourage total productivity.

7. CONCLUSION

Despite its late incorporation into the massive waves of worldwide immigration, Spain has nowadays become one of the European countries that receives most foreigners. The importance that this phenomenon has had in recent times, particularly in the developed world, has fuelled the debate about their economic effects. Traditionally, the literature in this regard has paid special attention to the potential substitution effect from more expensive native workers to a cheaper workface made up of immigrants. However, more recently, and probably motivated by the greater availability of data and a broader view of the phenomenon, a new perspective focusing on the diversity of immigrants has been incorporated into this debate. According to this literature, birthplace diversity may increase productivity by enabling the combination of different skills, ideas and perspectives.

The aim of this work is to provide a robust estimation of the impact of migration diversity on productivity in Spain at a regional level. In particular, we try to analyse how birthplace diversity has affected worker productivity in this economy during the period from 2008 to 2016, that is, once the economic crisis had ended. To study this question, we based our analysis on three different diversity indexes: the first, Fractionalization Index (Alesina *et al.*, 2003), reflects the probability that two randomly selected individuals from a population belong to different groups. The second, Entropy Index (Taagepera and Ray, 1977), provides a more accurate measure of diversity when the constituent groups are of different sizes. Finally, the third, Alesina Index (Alesina *et al.,* 2013), measures diversity strictly among those born abroad in a given place, instead of capturing heterogeneity among all individuals, natives and immigrants. In contrast to most of the previous literature and following the recommendations of Kemeny and Cooke (2018), we take into account the potential simultaneity between diversity migration and productivity by estimating the model through 2SLS. We instrumentalize the migration diversity using information on the ”predicted” change in the number of immigrants from each country in each AC (exogenous variable that fulfils the IV requirements), as proposed by Ottaviano and Peri (2006).

The results suggest a positive and significant correlation between migration diversity and native workers' productivity. This result is robust to both the unobserved regional heterogeneity and the presence of a two-way connection between productivity and birthplace diversity. Moreover, the outcome remains when the wages of the total population (without distinguishing between natives and immigrants) is used as a dependent variable. This confirms our main hypothesis of a positive productivity spillover from greater birthplace diversity, illustrating the danger of focusing on one single side of the coin in the political debate, when evaluating the consequence of migration.

Our findings further confirm the beneficial influence of a higher rate of young and skilled population on productivity. Therefore, given that more highly skilled labour may come from the entry of more trained workers, when data availability allows, more research should be conducted to take this issue into account before making a definitive evaluation of the total impact that heterogeneous immigration may have on recipient economies.

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9. ANNEXES

9.1 Distribution of immigrants in Spain by Autonomous Communities

Table 13. Distribution of immigrants in Spain by Autonomous Communities

	2008	2009	2010	2011	2012	2013	2014	2015	2016
Andalusia	12.79%	13.61%	12.69%	12.84%	13.44%	12.66%	12.48%	11.76%	11.32%
Aragon	3.81%	2.65%	2.77%	2.40%	2.07%	2.03%	1.93%	2.00%	2.15%
Asturias	1.33%	1.39%	1.45%	1.29%	1.24%	1.21%	1.06%	1.17%	1.15%
Balearic islands	3.70%	3.52%	2.97%	3.30%	4.20%	3.79%	3.50%	3.31%	3.31%
Canary Islands	5.31%	5.66%	5.95%	6.12%	7.51%	7.27%	7.21%	7.31%	7.57%
Cantabria	0.98%	0.79%	0.78%	0.75%	0.74%	0.67%	0.63%	0.65%	0.71%
Castilla and Leon	3.54%	3.43%	3.31%	3.10%	2.76%	2.72%	2.63%	2.44%	2.46%
Castilla la Mancha	3.79%	3.72%	3.67%	3.03%	2.47%	2.30%	2.46%	2.36%	2.39%
Catalonia	22.94%	22.06%	23.90%	24.04%	23.79%	23.42%	23.40%	23.80%	23.44%
Valencian Community	10.69%	12.07%	13.55%	12.75%	12.27%	13.22%	13.32%	12.96%	12.78%
Extremadura	0.71%	0.88%	0.84%	0.79%	0.73%	0.79%	0.66%	0.69%	0.62%
Galicia	3.15%	3.38%	3.32%	3.44%	3.02%	3.07%	2.97%	3.08%	3.30%
Madrid	19.22%	18.71%	17.00%	18.55%	18.48%	19.42%	20.65%	20.87%	20.94%
Murcia	3.23%	2.82%	2.26%	2.30%	2.40%	2.49%	2.31%	2.55%	2.62%
Navarre	1.27%	1.34%	1.23%	1.28%	1.21%	1.29%	1.19%	1.24%	1.34%
Basque Country	2.84%	3.25%	3.40%	3.43%	3.17%	3.21%	3.15%	3.27%	3.39%
The Rioja	0.68%	0.71%	0.90%	0.60%	0.50%	0.44%	0.45%	0.51%	0.51%

Source: Developed by author based on INE data.

9.2 Percentage of immigrants from each country who arrived in Spain in 2008 and 2016 over the total number of immigrants.

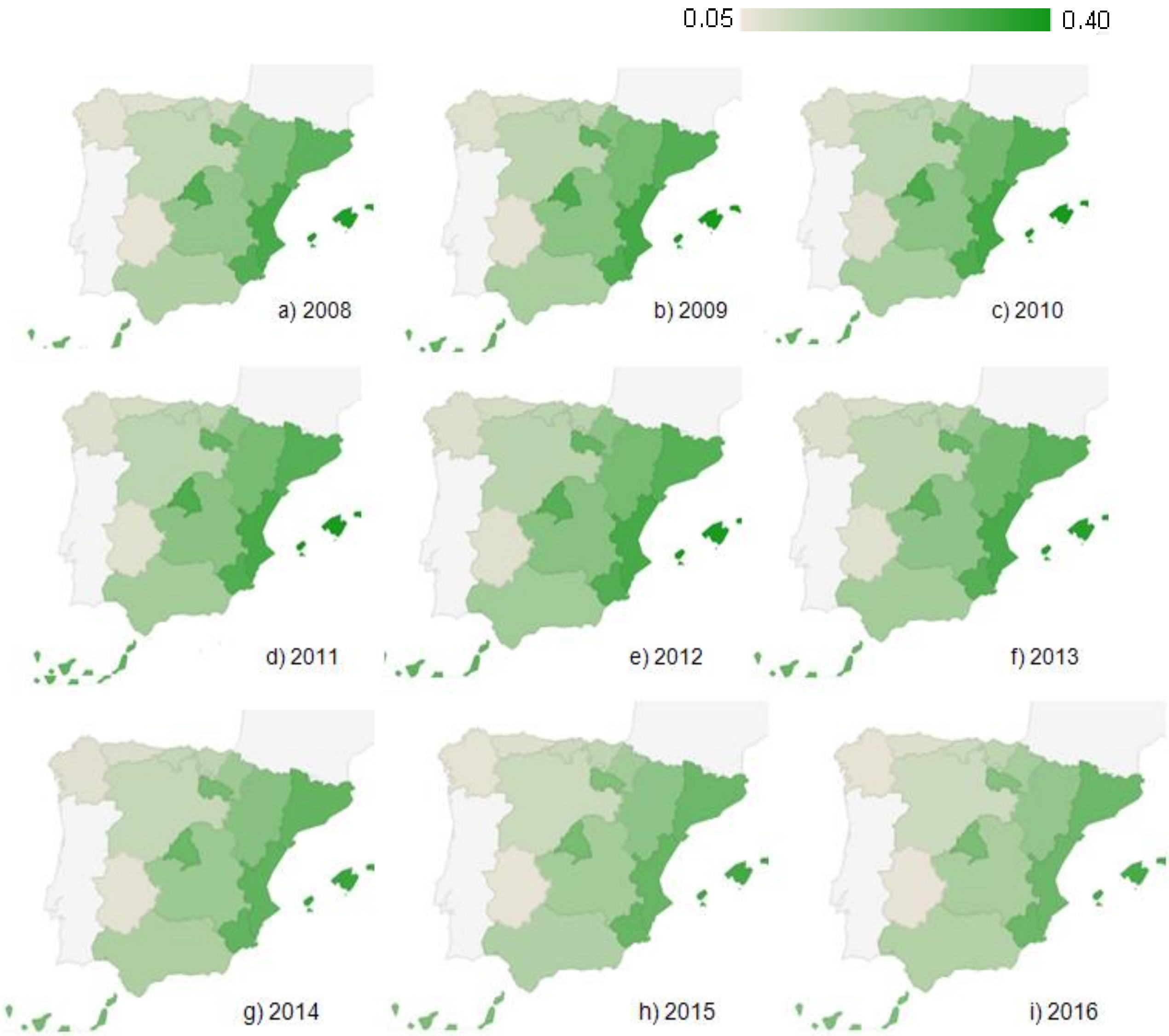
Table 14. Percentage of immigrants from each country who arrived in Spain in 2008 and 2016 over the total number of immigrants.

	2008	2016
Belgium	0.27%	0.72%
Bulgaria	1.85%	1.15%
Denmark	0.11%	0.18%
Finland	0.12%	0.21%
France	1.31%	2.31%
Ireland	0.19%	0.34%
Italy	2.58%	5.11%
Netherlands	0.60%	0.83%
Poland	1.13%	0.59%
Portugal	2.37%	1.38%
United Kingdom	3.84%	4.20%
Germany	1.79%	1.68%
Romania	10.77%	6.44%
Sweden	0.24%	0.43%
Lithuania	0.16%	0.25%
Norway	0.16%	0.26%
Switzerland	0.13%	0.27%
Ukraine	1.19%	1.71%
Moldova	0.40%	0.23%
Russia	0.85%	1.48%
Algeria	0.90%	1.18%
Gambia	0.40%	0.29%
Ghana	0.32%	0.24%
Guinea	0.28%	0.18%
Equatorial Guinea	0.29%	0.45%
Mali	0.58%	0.26%
Morocco	12.49%	6.73%
Mauritania	0.22%	0.16%
Nigeria	0.84%	0.29%
Senegal	1.52%	0.83%
United States of America	0.51%	1.68%
Mexico	0.67%	1.03%
Glen	0.05%	0.20%
Cuba	1.45%	1.42%
Honduras	0.80%	2.55%
Nicaragua	0.51%	0.93%
Dominican Republic	2.77%	2.14%
Argentina	2.44%	1.48%
Bolivia	1.87%	1.25%
Brazil	3.85%	2.24%
Colombia	6.22%	5.51%
Chile	0.90%	0.69%
Ecuador	5.25%	1.77%
Paraguay	3.23%	1.60%
Peru	3.90%	2.07%
Uruguay	0.85%	0.41%
Venezuela	1.44%	5.22%
Bangladesh	0.26%	0.41%
China	3.57%	2.52%
Philippines	0.81%	0.56%
India	0.81%	0.90%
Pakistan	1.42%	1.41%

Source: Developed by author based on INE data.

9.3 Maps of the Fractionalization Index by Autonomous Community in 2008-2016.

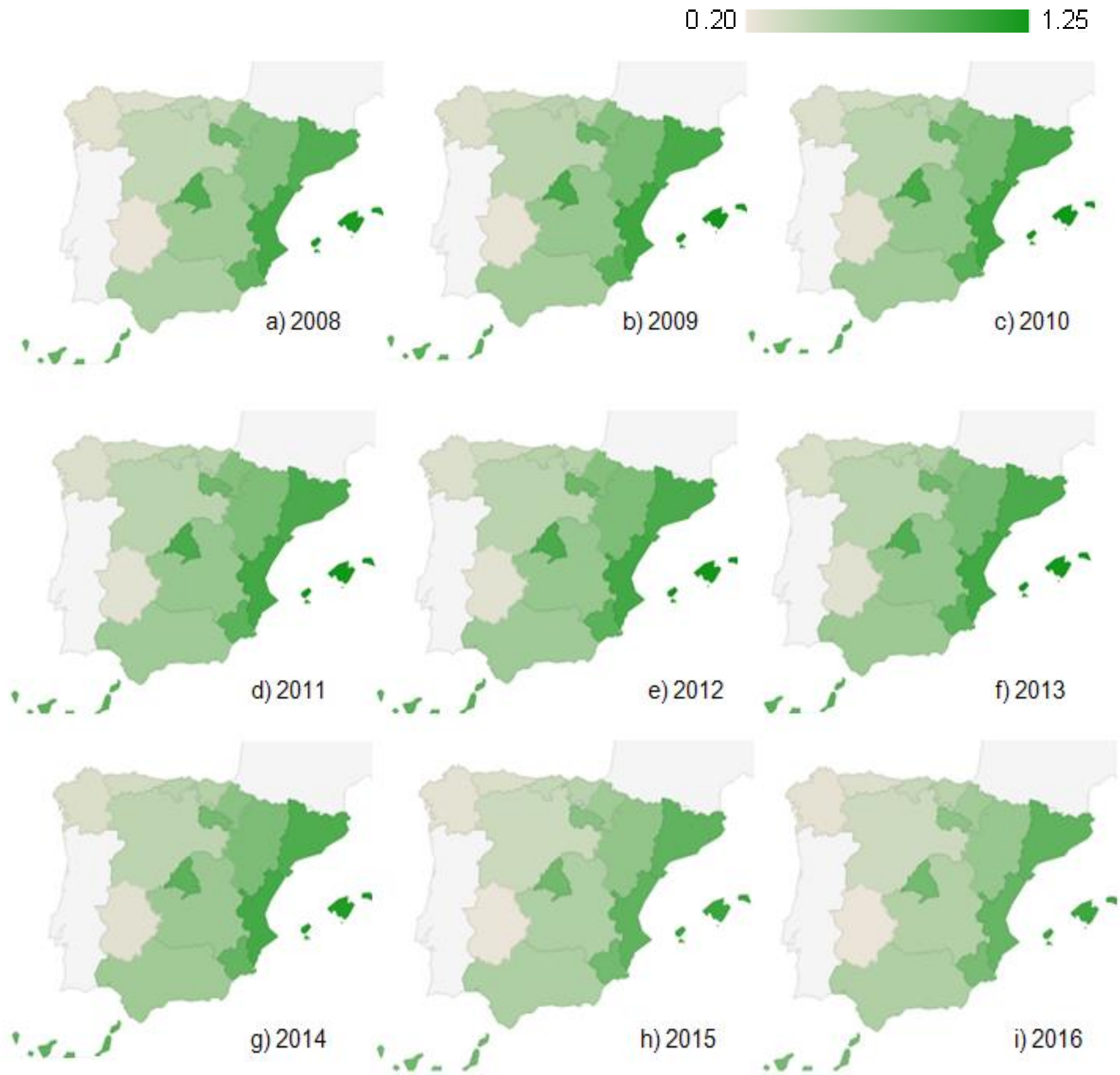
Figure 8. Maps of the Fractionalization Index by Autonomous Community in 2008-2016



Source: Developed by author based on INE data.

9.4 Maps of the Entropy Index by Autonomous Community in 2008-2016.

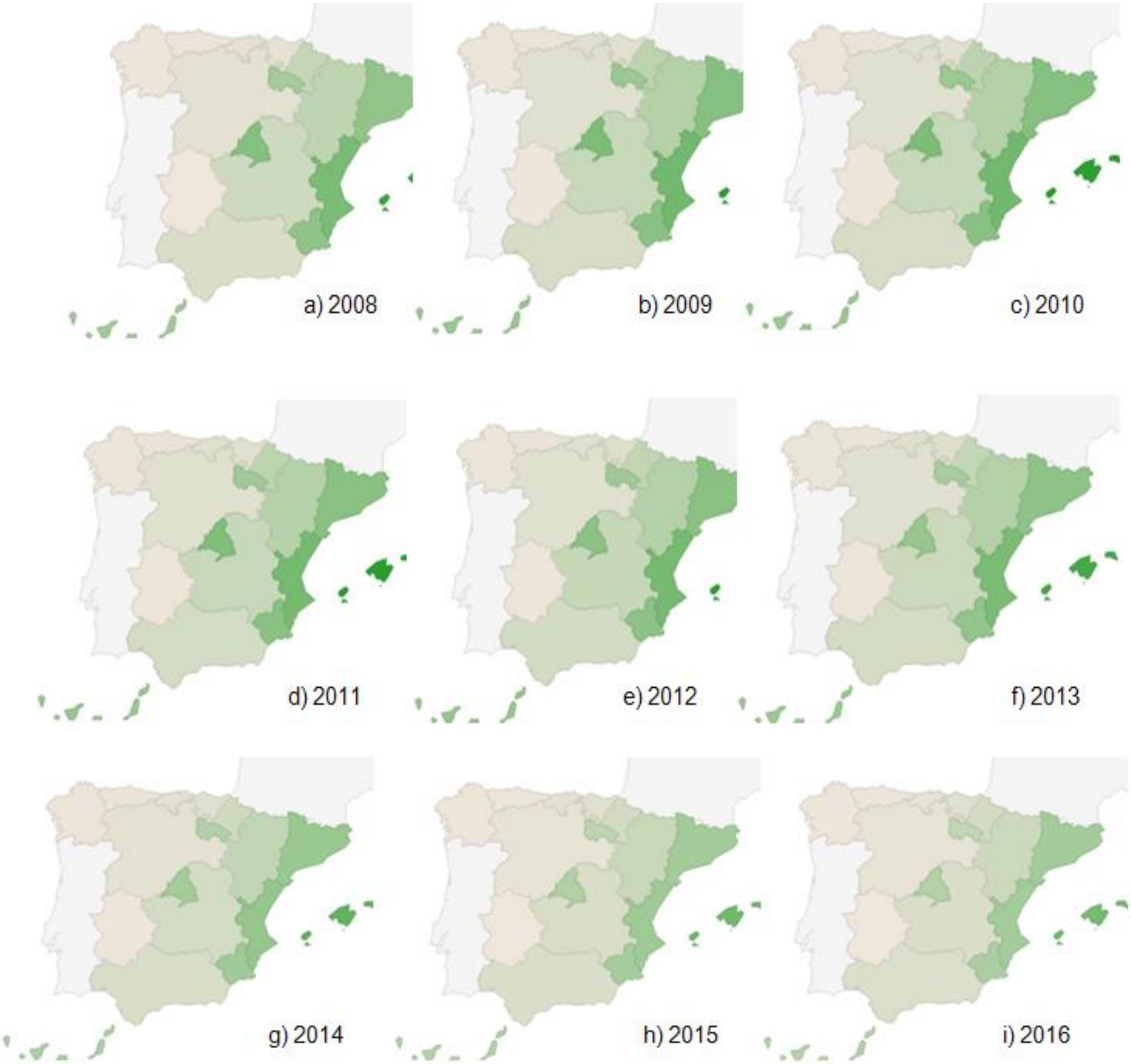
Figure 9. Maps of the Entropy Index by Autonomous Community in 2008-2016.



Source: Developed by author based on INE data.

9.5 Maps of the Alesina Index by Autonomous Community in 2008-2016.

Figure 10. Maps of the Alesina Index by Autonomous Community in 2008-2016.



Source: Developed by author based on INE data.

9.7 Average annual wage in Spain by nationalities.

Table15. Average annual wage in Spain by nationalities

	2008	2009	2010	2011	2012	2013	2014	2015
All nationalities	21,883 €	22,511 €	22,790 €	22,899 €	22,726 €	22,698 €	22,858 €	23,106 €
Spain	22,486 €	23,019 €	23,335 €	23,429 €	23,232 €	23,181 €	23,238 €	23,543 €
European Union less Spain	16,824 €	17,235 €	18,639 €	17,893 €	17,443 €	17,989 €	20,328 €	19,145 €
Rest of Europe	14,330 €	14,141 €	16,400 €	16,518 €	14,483 €	14,995 €	15,157 €	15,385 €
Latin America	13,862 €	14,059 €	14,650 €	14,713 €	14,280 €	13,909 €	14,714 €	14,339 €
Rest of the world	14,209 €	14,690 €	15,391 €	14,733 €	14,397 €	13,727 €	14,721 €	14,046 €

Source: Developed by author based on INE data.

9.8 Monthly wage cost by Autonomous Communities.

Table 16. Monthly wage cost by Autonomous Communities.

	2008	2009	2010	2011	2012	2013	2014	2015	2016
Andalusia	12.79%	13.61%	12.69%	12.84%	13.44%	12.66%	12.48%	11.76%	11.32%
Aragon	3.81%	2.65%	2.77%	2.40%	2.07%	2.03%	1.93%	2.00%	2.15%
Asturias	1.33%	1.39%	1.45%	1.29%	1.24%	1.21%	1.06%	1.17%	1.15%
Balearic islands	3.70%	3.52%	2.97%	3.30%	4.20%	3.79%	3.50%	3.31%	3.31%
Canary Islands	5.31%	5.66%	5.95%	6.12%	7.51%	7.27%	7.21%	7.31%	7.57%
Cantabria	0.98%	0.79%	0.78%	0.75%	0.74%	0.67%	0.63%	0.65%	0.71%
Castilla and Leon	3.54%	3.43%	3.31%	3.10%	2.76%	2.72%	2.63%	2.44%	2.46%
Castilla la Mancha	3.79%	3.72%	3.67%	3.03%	2.47%	2.30%	2.46%	2.36%	2.39%
Catalonia	22.94%	22.06%	23.90%	24.04%	23.79%	23.42%	23.40%	23.80%	23.44%
Valencian Community	10.69%	12.07%	13.55%	12.75%	12.27%	13.22%	13.32%	12.96%	12.78%
Extremadura	0.71%	0.88%	0.84%	0.79%	0.73%	0.79%	0.66%	0.69%	0.62%
Galicia	3.15%	3.38%	3.32%	3.44%	3.02%	3.07%	2.97%	3.08%	3.30%
Madrid	19.22%	18.71%	17.00%	18.55%	18.48%	19.42%	20.65%	20.87%	20.94%
Murcia	3.23%	2.82%	2.26%	2.30%	2.40%	2.49%	2.31%	2.55%	2.62%
Navarre	1.27%	1.34%	1.23%	1.28%	1.21%	1.29%	1.19%	1.24%	1.34%
Basque Country	2.84%	3.25%	3.40%	3.43%	3.17%	3.21%	3.15%	3.27%	3.39%
The Rioja	0.68%	0.71%	0.90%	0.60%	0.50%	0.44%	0.45%	0.51%	0.51%

Source: Developed by author based on INE data.