UNIVERSITAT
ROVIRA I VIRGILI
DEPARTAMENT D'ECONOMIA

creip
CENTRE DE RECERCA EN ECONOMIA
INDUSTRIAL I ECONOMIA PÚBLICA

WORKING PAPERS

Col·lecció "DOCUMENTS DE TREBALL DEL
DEPARTAMENT D'ECONOMIA - CREIP"

Location Determinants of New Firms: Does Skill Level of Human Capital Really Matter?

Josep-Maria Arauzo-Carod

Document de treball nº -8- 2011

DEPARTAMENT D'ECONOMIA – CREIP
Facultat de Ciències Econòmiques i Empresarials

UNIVERSITAT
ROVIRA I VIRGILI
DEPARTAMENT D'ECONOMIA

(creip)
CENTRE DE RECERCA EN ECONOMIA INDUSTRIAL I ECONOMIA PÚBLICA

Edita:

Departament d'Economia
www.fcee.urv.es/departaments/economia/public_html/index.html
Universitat Rovira i Virgili
Facultat de Ciències Econòmiques i Empresarials
Avgda. de la Universitat, 1
43204 Reus
Tel.: +34 977 759 811
Fax: +34 977 300 661
Email: sde@urv.cat

CREIP
www.urv.cat/creip
Universitat Rovira i Virgili
Departament d'Economia
Avgda. de la Universitat, 1
43204 Reus
Tel.: +34 977 558 936
Email: creip@urv.cat

Adreçar comentaris al Departament d'Economia / CREIP

Dipòsit Legal: T -1092- 2011

ISSN 1988 - 0812

DEPARTAMENT D'ECONOMIA – CREIP
Facultat de Ciències Econòmiques i Empresarials

Location Determinants of New Firms: Does Skill Level of Human Capital Really Matter?*

Josep-Maria Arauzo-Carod (♣,♦): josepmaria.arauzo@urv.cat

Abstract:

This paper is about the role played by stock of human capital on location decisions of new manufacturing plants. We analyse the effect of several skill levels (from basic school to PhD) on decisions about the location of plants in various industries and, therefore, of different technological levels. We also test whether spatial aggregation level biases the results and determine the most appropriate areas to be considered in analyses of these phenomena. Our main statistical source is the Register of Manufacturing Establishments of Catalonia (REIC), which has plant-level microdata on the locations of new manufacturing plants.

Keywords: agglomeration economies, industrial location, human capital, count-data models, spatial econometrics.

(♣) Universitat Rovira i Virgili, Departament d'Economia (QURE-CREIP); Av. Universitat, 1; 43204 – Reus (Catalonia, Spain); Phone +(34) 977 758902; Fax +(34) 977 759 810.
(♦) Institut d'Economia de Barcelona (IEB); Av. Diagonal, 690; 08034 – Barcelona (Catalonia, Spain)

This study was partially funded by SEJ2010-19088/ECON, SEJ2010-16934/ECON, the "Xarxa de Referència d'R+D+I en Economia i Polítiques Públiques", the SGR programme (2009-SGR-322) of the Catalan Government, and the PGIR programme (N-2008PGIR/05) of Rovira i Virgili University. This article has benefited from discussions with Á. Alañón, D. Liviano and M. Manjón. We are grateful to seminar participants at "Regional Competitiveness and International Factor Movements" (INFER & LEO – Université d'Orléans). Any errors are, of course, our own.

1. Introduction

Both academics and policymakers have shown a growing interest in the analysis of decisions regarding the location of new plants. For academics, the phenomenon deserves attention because of there is still great uncertainty surrounding the process of making location decisions, mainly in terms of the methodologies used but also regarding specific determinants and spatial aggregation issues. For policymakers, the main concerns are related to the effects of plant location on urban and regional growth in terms of employment growth and economic dynamism, but they are also interested in identifying location determinants in order to implement effective entry-promotion policies.

In light of this interest, there is still room for new contributions and, specifically, for the analysis of how local[1] characteristics contribute to new entries. Of these local characteristics, there is one for which there are no conclusive results from empirical work: human capital, and specifically, the skill level of human capital in terms of formal education, which could be indicative of labour-force quality. Many scholars have introduced human-capital characteristics into their estimations but, unfortunately, the existing results are very heterogeneous (although they roughly indicate that human capital is of minor importance among the determinants of new firm location) and do not clearly identify the effect of human capital on entries. Furthermore, nothing has been said in the literature about where to check for the effect of human capital on location decisions (e.g., In the same areas where plants are located? In neighbouring areas? In a wider geographical area?) and whether the effects are different for different industries (e.g., Are firms from different industries looking for the same types of skills when choosing a site, or is the search process shaped by industry specificities?). Because of the shortcomings of previous empirical contributions, there is a lack of consistency that has enormous implications for policymaking, since no clear policies can be set to promote firm entry, apart from some

[1] The word "local" has a range of different meanings, from small units such as municipalities to larger areas such as counties or travel-to-work areas.

general considerations about improving the stock of human capital. In this paper, we aim to better illustrate this relationship and to provide empirical evidence for the effect that different skills (in terms of formal education) have on decisions about the location of new manufacturing plants. Specifically, two research questions are addressed in this study: *i)* Are previous empirical findings that human-capital stock is of minor importance due to the inappropriate selection of spatial units in the analysis of human capital? *ii)* Once the previous shortcomings have been resolved, is it possible to accurately determine whether location decisions of new plants are shaped by industry-specific characteristics, insofar as specific human-capital stock is considered?

We have structured the paper as follows. In Section 2 we discuss the literature on location determinants of manufacturing firms and, specifically, on the role played by human capital. In Section 3 we present the model and the data. In Section 4 we present and discuss the results. Finally, in Section 5 we summarise our main conclusions.

2. Literature review

2.1 Determinants of location decisions

Empirical studies of location decisions of manufacturing firms are very heterogeneous in terms of methodology, range of industries, spatial areas considered, types of entering firms and determinants. Arauzo-Carod et al. (2010) recently summarised the main contributions by grouping them by method (discrete-choice models and count-data models) and by theoretical approach (neoclassical, institutional and behavioural factors).

The empirical evidence reviewed by Arauzo-Carod et al. (2010) shows that most studies in this field highlight the importance of agglomeration economies, but also that there are other important determinants that should be taken into account, such as transport infrastructures, technological level of entering firms, taxes, environmental regulations, entry-promoting policies, behavioural issues and human-capital characteristics.

2.2 Territorial human capital and firm location

The effect of educational level on firms' location decisions is twofold: some scholars have demonstrated a positive relationship (Alamá-Sabater et al. 2011, Alañón et al. 2007, Cheng and Stough 2006, Egeln et al. 2004, Gabe and Bell 2004, Holl 2004c, Holl 2004b, Coughlin and Segev 2000, Smith and Florida 1994, Woodward 1992, Luger and Shetty 1985),[2] while others have found a negative effect (Arauzo-Carod 2009, 2005; Arauzo-Carod and Manjón-Antolín 2004; Cieślik 2005; Holl 2004a; Guimarães et al. 2000; Schmenner et al. 1987; Bartik 1985, 1988) and still others have found mixed effects (Arauzo-Carod and Viladecans 2009, Arauzo-Carod 2008). The empirical evidence therefore seems to be inconclusive and contradictory, and consequently there is room for more empirical work to identify some stylised facts about the effect of educational level on the location of new plants.[3]

On the basis of this (apparently) contradictory evidence, we can ask some key questions: *i*) Should the educational level of the whole population be measured, or only that of the working population? *ii*) Should skill levels be analysed in the areas where firms locate, or in neighbouring areas? *iii*) Should industry-specific effects be identified (if skilled human capital is considered a production input, its weight differs considerably among industries)? Additionally, we should consider that higher educational levels are usually correlated with higher wages, so depending on its economic activity, a firm should consider whether to accept paying such wages.

[2] Some of these papers analyse only the location decisions of high-tech firms (Egeln et al. 2004, Luger and Shetty 1985), so it seems reasonable to find a positive effect, although Arauzo-Carod (2009) also analyses only the entry of high-tech firms and finds a negative effect.
[3] Previous contributions are also highly heterogeneous in terms of methods, approaches, detail level of the analysis, industry aggregation and focus.

What population should be analysed and how should human capital be measured?

Measurements of individual educational levels that can influence new firms' location decisions should take into account size differences among territorial units, and the easiest (and most popular) way of doing this is to standardise educational variables by some indicator of territory size, usually population or workers. It appears that scholars just find and use available data (e.g., people with tertiary education / total population), but it is also reasonable to argue that behind each indicator there are some theoretical underpinnings, even if the importance of data constraints is acknowledged. Specifically, standardising the number of educated individuals by total population has slightly different implications, in terms of the nature of the effect, than standardising the number of educated workers by total workers. Whereas focusing on population implies taking into account the potential human-capital stock of a territory (regardless of whether this potential is being used), focusing only on workers implies a short-term approach and considers only the current stock of human capital used for economic purposes. The human-capital measures included in this dataset refer to the number of individuals with the specified characteristics relative to the number of jobs (in 2001).

Empirical evidence shows that measures of human capital are very heterogeneous in terms of how human-capital variables are measured:

- Availability of education institutions: the presence of a local high school (Gabe and Bell 2004).[4]
- Number of schooling years: the average years of education for individuals older than 25 (Arauzo-Carod 2008), the mean years of education (Holl 2004b),[5] the median years of school completed by the adult population (Woodward 1992), the number of manufacturing

[4] Gabe and Bell (2004) use a more detailed approach and they also compute local public spending on education. We do not take those expenditures into account because they refer to input measures, and in this study we concentrate on output measures.
[5] Holl (2004b) uses a more complete approach. She considers not just educational level (mean years of education) but also work experience.

employees with 10 or more years of education (Hansen 1987), median years of education (Bartik 1985).

- Percentage of the population that reaches intermediate educational levels: the percentage of the adult population with at least a junior high school education (Cheng and Stough 2006), the ratio of high school students to all people aged 15–18 (Cieślik 2005), the percentage of the regional labour force with no more than a secondary school education (Holl 2004a), the percentage of the population age 25 or over with at least a high school diploma (Coughlin and Segev 2000), the proportion of the labour force with an elementary (secondary) education (Guimarães et al. 2000), the percentage of the workforce that has completed high school (Schmenner et al. 1987).
- Percentage of the population that reaches intermediate-high educational levels: the percentage of the labour force that has completed secondary and tertiary education (Alamá-Sabater et al. 2011), the percentage of the population with a university degree and the percentage of the population that has completed at least secondary school (Arauzo-Carod and Viladecans 2009), the percentage of the population over ten years old that has completed at least secondary education (Alañón et al. 2007), the percentage of the population with a high school degree or above (Smith and Florida 1994).
- Percentage of the population that reaches high educational levels: the percentage of the population with a university degree (Arauzo-Carod 2005), the percentage of the labour force with higher education (Holl 2004c).
- Number of individuals that reach specific educational levels: number of inhabitants with a university degree (Egeln et al. 2004).
- Density of human capital: density of high-tech workforce (Arauzo-Carod 2009), number of people with medium and high levels of education per km^2 (Arauzo-Carod and Manjón-Antolín 2004).
- Other measures: percentage of white-collar workers in labour force (Luger and Shetty 1985).

Where and how should educational levels be measured?

As mentioned above, scholars have measured educational attainment for different types of populations (e.g., resident population, working population, active population, etc.) and geographical levels (e.g., cities, counties, metropolitan areas, provinces, regions, etc.) when using this characteristic as a determinant for the location of new plants. However, most existing empirical evidence offers no theoretical arguments to support these measures (e.g., favouring local over regional measurement of human capital), so it seems that data availability unfortunately drives the way in which educational level is measured. In other words, scholars just find available measures without questioning whether the geographical level of aggregation or the educational level in question were the most appropriate measures.

Obviously, this heterogeneity could bias the results and make comparisons more difficult, because the spatial areas used range from small geographical units such as municipalities to larger ones such as US states:

- Local level: municipalities in Spain (Alamá-Sabater et al. 2011, Alañón et al. 2007), municipalities in Catalonia (Arauzo-Carod 2008, 2005; Arauzo-Carod and Manjón-Antolín 2004), municipalities in Maine (Gabe and Bell 2004), *concelhos* in Portugal (Guimarães et al. 2000).
- County level: counties (*comarques*) in Catalonia (Arauzo-Carod 2009, 2008; Arauzo-Carod and Manjón-Antolín 2004), German districts (*Kreise*) (Egeln et al. 2004), US counties (Coughlin and Segev 2000, Smith and Florida 1994, Woodward 1992).
- Travel-to-work areas: travel-to-work areas in Catalonia (Arauzo-Carod 2008).
- Metropolitan areas: Spanish metropolitan areas (Arauzo-Carod and Viladecans 2009), Greater São Paulo and surrounding areas in Brazil (Hansen 1987).
- Province level: provinces in China (Cheng and Stough 2006), NUTS3 in Portugal (Holl 2004a, 2004b), NUTS3 in Spain (Holl 2004c).

- Regional level: Polish regions (Cieślik 2005).
- State level: US states (Schmenner et al. 1987, Bartik 1985, Luger and Shetty 1985).

Within the theoretical discussion about the geographical areas that should be taken into account, Woodward (1992) argues that although educational attainment has traditionally been measured at a large geographical level (specifically, US states), educational levels usually vary considerably when smaller units (e.g., counties) are considered, so smaller areas should be preferred for an empirical analysis. Apart from Woodward, however, there has been no discussion of whether such measures are appropriate, and researchers usually use whatever data is available.

Despite the previous methodological approaches, it seems reasonable to assume that new plants take into account the availability of skilled labour accessible to the new location, so the spatial aggregation level of human-capital variables really does matter. Under this assumption, we will consider that new firms look at human-capital availability within an area big enough (a radius of 60 km) to account for spatial dependence phenomena among individuals and firms (see Section 4.1). The point is that firms look at skilled labour both at the local level and in neighbouring areas.

<u>How should industry-specific effects be taken into account?</u>

It seems reasonable to assume a direct relationship between the technological level of a firm (or industry) and the skill level of its workers, so one could expect that low-technology firms would depend on low-skilled labour whereas high-technology firms would depend on high-skilled labour. Surprisingly, most scholars do not take into account such industry-specific requirements, instead measuring educational level without distinguishing by industry. But if we assume that educational requirements differ by industry, mixing all the industries together produces biased effects.

Apart from the obvious fact that the labour force of a firm (or industry) is a combination of different skills (in a specific proportion) that depends on the technological level of the firm (or industry), one should expect that when choosing a site low-tech firms look (mainly) for the availability of unskilled workers, while high-tech firms look (mainly) for the availability of skilled workers. Holl (2004a) uses data from Portugal to find empirical evidence of low-tech skills. As a proxy for the low labour force qualification, she computes the percentage of the labour force with only secondary education, but she uses this variable for all entering plants regardless of technological level. The reported effect on the number of new plants for the whole sample is negative (both for strictly new plants and for relocated ones), but for plants with five or more employees the effect remains negative but is no longer significant. With the same dataset, Holl (2004b) considers a measure of skills that takes into account both education and work experience[6] and analyses its influence over a wide range of industries (all manufacturing, 12 manufacturing industries, construction, all services and 9 service industries). Surprisingly, her results are more clear for the more aggregated industries because her measure of education has a significant positive effect on entries in manufacturing, construction and services, while for specific industries (in manufacturing and services) the results are less significant and, in any case, mixed: positive for machinery, textiles/footwear, retail trade and non-market services, but negative for transport and communication. In a similar approach, Arauzo-Carod and Viladecans (2009) use a general measure of human capital—the percentage of the population with a university degree and the percentage of the population with (at least) a secondary school education—to estimate new manufacturing plant entries for industries of high, intermediate and low technological level in Spanish metropolitan areas. Their results show that medium-skilled human capital has a positive effect on almost all industries and that high-skilled human capital has a (mainly) negative effect, especially for industries with an intermediate technological level. Also focusing on Spain, Holl (2004c) takes into account the percentage of the labour force with higher education and finds a

[6] Labour force qualification equals mean years of schooling plus mean years of work experience (Holl, 2004b).

positive effect for all manufacturing activities, but this significant effect is maintained at the two-digit level only for some manufacturing activities (minerals, metal products, machinery, food and beverages, paper and printing, and wood and furniture).

In a similar approach, Arauzo-Carod (2005) uses the same measure of human capital (percentage of the population with a university degree) to analyse entries in different industries and concludes that the negative effect that he found when analysing all entries together only holds for industries with differentiated products; the effect is positive and not significant for natural resources, labour-intensive industries and R&D-intensive industries, and negative and not significant for industries with economies of scale.[7]

It is for high-tech firms that one could expect a clear positive relationship between location and availability of skilled labour, as has been demonstrated, among others, by Audretsch and Lehmann (2005), who explain that the number of knowledge-based start-ups clustered around German universities "is positively influenced by the knowledge output of the respective university and the innovative capacity of the region", and by Egeln et al. (2004) about spin-offs created from public research institutions. But there is also empirical evidence (Luger and Shetty 1985) that shows some mixed results (depending on the industry) and even points in the opposite direction (Arauzo-Carod 2009).

In addition to the aforementioned considerations of employee skill level, one could argue that there is also a wage effect, but wages and educational levels tend to be highly correlated (see Table A.1 in the Appendices), which in some cases could make it harder to determine whether a skill effect or a wage effect is driving a firm's decisions. Specifically, this means that even if the effect on entries can be easily identified (i.e., it positively or negatively influences the

[7] Arauzo-Carod (2005) also analyses aggregated entries by categorising firms by size and finds that the negative and significant effect on them is maintained only for the smallest ones (up to 49 workers), whereas the effect is negative but not significant for the medium ones (50 to 99 workers) and positive but not significant for the biggest ones (more than 99 workers).

number of new plants), it would not be clear whether the effect was caused by a high (low) level of educational attainment or by a high (low) wage level.

3. Data and model

3.1 Data

The data in this paper refer to Catalonia,[8] an autonomous region in northeastern Spain whose capital is Barcelona. The data include one dataset about the location of new plants (dependent variable) and another dataset about the territorial characteristics of human capital (independent variables), in addition to some control variables.

The dataset about the location of new plants is the Register of Manufacturing Establishments of Catalonia (REIC), which has plant-level microdata on the location of new manufacturing plants. Supplied by the Catalan Government (Ministry of Innovation, Universities and Enterprise), the REIC provides data about both new and relocated plants. Since both types of plants may be attracted to an area by the same variables, we use both types without distinction.[9] This dataset includes 4,282 manufacturing plants with codes 12 to 36 (see NACE-93 industry classifications in Table A.2 of the Appendices) that were located in Catalonia between 2001 and 2005.

[INSERT FIGURE 1 HERE]

Figure 1 shows that most of these plants are concentrated around the metropolitan area of Barcelona and other major cities, but a different pattern arises if we disaggregate entries by OECD classification (Figure 2). Although the importance of the Barcelona metropolitan area still holds, some specificities

[8] Catalonia has about 7 million inhabitants (15% of Spain's population) and an area of 31,895 km^2. It accounts for 19% of the Spanish GDP.
[9] See Manjón-Antolín and Arauzo-Carod (2011) for a detailed analysis of the interrelations between locations and relocations.

appear, such as a greater spread of entries in natural-resource-intensive sectors and a higher concentration of R&D-intensive sectors.

The dataset about human capital is mainly taken from Trullén and Boix (2005), the Catalan Statistical Institute (IDESCAT) and the Catalan Cartographical Institute, and it includes information (from 2001) for all 946 Catalan municipalities. The measures of human-capital education (from 2001) included in this dataset refer to the number of individuals with the specified characteristics relative to the number of jobs:

- Illiterate people (ILLI)
- Incomplete primary education (INCOMPE)
- Primary education (PRIMEDU)
- Middle school (MIDSCH)
- Technical high school 1 (TECHS1)
- Technical high school 2 (TECHS2)
- High school (HIGHS)
- Intermediate university degree (MEDUNI)
- Advanced university degree (HIGHUNI)

Additionally, we include:

- Average number of years of education for individuals over age 25 (YEARS)
- Spatial lags of the above-defined human-capital variables: W_ILLI, W_INCOMPE, W_PRIMEDU, W_MIDSCH, W_TECHS1, W_TECHS2, W_HIGHS, W_MEDUNI, W_HIGHUNI and W_YEARS.

[INSERT TABLE 1 HERE]

We also include some control variables that are widely used in empirical location literature, such as:

- Agglomeration economies: population density (DENS)
- Transport infrastructure: distance to the provincial capital (PROVCAP)

- Geographical and administrative issues: shore-line areas (COAST), county capitals (CAP)
- Industrial mix: percentage of manufacturing jobs (JOB_IND), concentration index (CI)[10] and percentage of small firms (SMALL)[11]

To check for some type of correlation among explanatory variables, we provide a correlation table that shows that there are no major problems with the human-capital variables (Table 2).[12] In accordance with these results, we were able to use all of the human-capital measures in the econometric estimation.

[INSERT TABLE 2 HERE]

It is important to have an overview of the spatial distribution of human-capital variables, since one could expect the educational levels of the population to be unevenly distributed across the analysed territory. Figure 3 shows the educational spatial distribution by municipality, taking into account various measures of skills.

[INSERT FIGURE 3 HERE]

Generally speaking, the data in Figure 3 show a spatially heterogeneous distribution of skills, which strongly determines spatial differences in attractiveness for firms according to skill requirements. There is a slight concentration of more educated people around the metropolitan area of Barcelona and in the wealthy areas of the northeast and northwest, where income levels are above the mean. Additionally, there are specific municipalities with high educational levels that usually correspond to county capitals and surrounding areas. The inland and southern areas (usually the most agriculture-oriented) have lower educational levels. Figure 3 depicts the labour market from

[10] CI ranges from 0 to 1, where 0 means that the municipality is not at all specialised in any industry and 1 means that the municipality is highly specialised.
[11] SMALL refers to firms with up to 50 workers.
[12] Only for YEARS and PRIMEDU is the correlation between variables slightly high.

the perspective of skill supply but obviously says nothing about the demand for skills (we have no spatial distribution of skill requirements for jobs), nor do we assume that all workers' educational levels fit perfectly with the educational level required for their jobs. Therefore, we acknowledge that these data could hide some cases of overeducation, but the purpose of this paper is not to address this issue. We examine the educational levels of the population merely to determine whether new firms can access different levels of knowledge depending on the geographical area where they decide to locate and whether these location decisions are industry-specific (i.e., different types of industries have different types of requirements in terms of employees' skills).

3.2 Model

Following previous empirical contributions on the location determinants of new plants (see Arauzo-Carod et al. 2010 for a review), we use count-data (CD) models to identify location determinants. These models are extremely convenient for dealing with large datasets about possible location alternatives (e.g., municipalities).

Because descriptive statistics about entrants at the two-digit industry level (Table 3) show signs of both overdispersion and zero inflation,[13] we decided that a basic CD model such as a Poisson model should not be considered.

[INSERT TABLE 3 HERE]

The CD models expected to fit best with this data are those that account for the aforementioned specificities (i.e., negative binomial, zero-inflated Poisson and zero-inflated negative binomial),[14] so we first estimated a baseline model

[13] Overdispersion and zero inflation are typical features of data about the location of new plants. Specifically, they suggest a high heterogeneity among sites, which means that there are important differences in the number of plants that each site (municipality, in this case) receives and that some (sometimes most) sites do not receive any entries at all. For a technical analysis of the implications of overdispersion and zero inflation, see Cameron and Trivedi (1998).

[14] Nevertheless, we also estimate a Poisson model in order to compare results with the (a priori) more suitable models.

without any industry effect and selected the one that fit best using the Akaike information criterion (AIC), the log-likelihood function (LOG) and the Vuong test.

[INSERT TABLE 4 HERE]

Table 4 shows the results of these statistics, which suggest the use of zero-inflated negative binomial models. Negative-binomial models fit better than the rest and, of these, the zero-inflated negative binomial is the one that performed best, according to AIC and LOG. The Vuong test also favoured the zero-inflated negative binomial over the negative binomial model.

4. Empirical approach and results

4.1 Spatial exploratory analysis

In order to account for spatial dependence, we also considered the spatially lagged variables of the human-capital-independent variables. Specifically, these are estimated as follows: $W\_X = WX$, where X is a matrix that contains the human-capital-independent variables and W is an appropriate (row-standardised) spatial-neighbour matrix. W can be approached in different ways (distance-based neighbours, *k*-nearest neighbours, contiguous neighbours and inverse-distance-based neighbours); nevertheless, in a departure from previous research on the same geographical area, we decided to build W as a distance-based matrix and, specifically, using a neighbouring criterion of 60 km (i.e., two municipalities are considered neighbours if they fall within 60 km of one another, measured from the centroid of each municipality).[15] Once W is identified, we can calculate whether the variables are spatially related. In order to do this, we calculate both global and local measures of spatial

[15] Arauzo-Carod and Manjón-Antolín (2011) analyse the empirics of the location of new manufacturing plants in Catalonia and try to determine the geographical scope that should be considered when dealing with location issues. They compare several W-matrixes with criteria ranging from 10 km to 100 km using the log-likelihood function, the Akaike information criterion and the chi-square goodness-of-fit test, and they find that the best fit was achieved by the 60 km W matrix. Because their dataset is exactly the same as the one used in this paper, we can therefore use a 60 km weight matrix as a neighbourhood criterion.

autocorrelation: Moran's I (Moran, 1948) and the Local Index of Spatial Association (LISA), respectively.

$$Moran's\,I = \frac{\dfrac{\sum_{i \neq j} c_{ij}(x_i - \bar{x})(x_j - \bar{x})}{W}}{\dfrac{\sum_i (x_i - \bar{x})^2}{n}} \qquad \text{where } W = \sum_{i \neq j} c_{ij}$$

The numerator is the covariance between contiguity observations (each contiguity weight is c_{ij}/W). This covariance is null if there is no spatial autocorrelation, positive if there is positive spatial autocorrelation and negative if there is negative spatial autocorrelation. The covariance is normalised using the total variance of the series (denominator). The values of Moran's I are interpreted as follows: if they range from -1 to 0, there is negative spatial autocorrelation; if it is 0, there is a random distribution of the variable; and if they range from 0 to 1, there is positive spatial autocorrelation. Table 5 shows the Moran's I results for the human-capital-independent variables.

[INSERT TABLE 5 HERE]

Beyond global spatial autocorrelation measures, it is important to notice that spatial dependence phenomena could be local in nature rather than global, so we must check whether results are driven by the general characteristics of the data or the territory under analysis or, on the contrary, driven by specific local characteristics that exist only in some areas. Accordingly, we have estimated a Local Index of Spatial Association (LISA) for the variables (Figure 4), where red areas indicate high-high spatial autocorrelation, dark blue areas indicate low-low spatial autocorrelation, light blue areas indicate low-high spatial autocorrelation, light red areas indicate high-low spatial autocorrelation and white areas indicate that spatial autocorrelation is not significant.

[INSERT FIGURE 4 HERE]

The maps in Figure 4 show that spatial dependence differs by geographical area and human-capital variable. Specifically, whereas in the southern areas there is low-low spatial autocorrelation for variables measuring higher levels of education and high-high spatial autocorrelation for variables measuring lower levels of education, in the northwestern areas the opposite occurs, since the spatial autocorrelation tends to be negative for low-education variables and positive for high-education variables. The maps of local spatial autocorrelation taken together with Figure 4 show quite different (and, to a certain extent, homogeneous) areas: northwest, northeast, south and, sometimes, centre (around the metropolitan area of Barcelona). For most of the explanatory variables, these areas show a different pattern in terms of local spatial autocorrelation and are separated from the rest of Catalonia by wide swaths in which there is no local spatial autocorrelation. Accordingly, it seems that the spatial dependence of human-capital variables is driven by spatial homogeneity at larger areas. This result appears to be reasonable, given the spatial distribution of the public education infrastructure, which is designed for areas larger than municipalities.

4.2 Econometric estimation

As seen in the previous section, estimation tests suggest using the zero-inflated negative binomial model.[16] We will first estimate a baseline model without industry-specific effects (Table 6) in order to see general trends regarding the influence of several human-capital educational levels[17] on the location decisions of new manufacturing plants. Later, we will introduce both spatial effects and industry effects in order to account for these issues. Specifically, we will show an estimation considering OECD classification of manufacturing industries according to sources of competitiveness both with and without spatial effects (Table 7).

[16] Applications of the zero-inflated negative binomial model are quite recent in empirical location literature and include those of Manjón-Antolín and Arauzo-Carod (2011), Arauzo-Carod (2008) and Kim et al. (2008).

[17] In addition to current measures of human capital, we also calculated some interactions among them but the results were roughly the same.

[INSERT TABLE 6 HERE]

Our first estimation does not take into account industry-specific effects. While it can surely be strongly criticised, this assumption can be useful as a starting point. The results of this estimation (Table 6) show that while almost all control variables are significant and have the expected sign, almost all human-capital variables lack significance. Specifically, the results show that the control variables of population density (DENS), specialisation level (CI) and percentage of manufacturing jobs (JOB_IND) have positive effects on the number of new plants, which supports previous empirical evidence about the positive effect of agglomeration economies on location decisions (Gabe, 2003). Likewise, being a county capital (CAP) and being located near the sea (COAST) have positive effects, while a greater distance from the provincial capital (PROVCAP) and a higher percentage of small firms (SMALL) is associated with a lower number of new plants. Nevertheless, our results show that the human-capital variables—except for the average number of years in education (YEARS), which has a positive and significant effect in one of the estimations—are mainly negative and not significant. These results could suggest that human-capital levels at the local level have no effect on firms' location decisions, but we consider that this conclusion is strongly biased by *i)* not taking into account industry-specific effects, which are correlated with different types of educational levels, and by *ii)* trying to estimate the location decisions of new plants at the local (municipality) level by considering only the stock of human capital at the local level, without taking into account the stock in neighbouring municipalities.

Accordingly, when spatially lagged human-capital variables are introduced, the estimation results become more reasonable because although human-capital variables measured at the local level remain not significant, the corresponding spatially lagged variables are all positive and significant. Our assumption is that human-capital variables should not be measured at the local level but rather over a wider spatial area, since firms look for workers not only in the specific sites (municipalities) where they are located, but also in the surrounding areas. Moreover, from the workers' point of view, the labour market (i.e., the area in which they commute daily) is larger than local. Therefore, if we measure stock of human capital at a more appropriate spatial level, this bias should be lower.[18]

The estimation also needs to address industry-specific issues, since it is not reasonable to assume that firms from different industries require the same types of workers in terms of educational attainments (e.g., considering differences such as knowledge intensity or skill composition of the labour force). We must therefore take into account industry effects.

[INSERT TABLE 7 HERE]

Generally speaking, our results are quite similar to the previous estimation in terms of the lack of significance of human-capital variables measured at the local level and the expected and significant results for most of the control variables, although there are several industry-specific effects that create a slightly different picture. Interestingly, differences arise when spatially lagged variables are introduced. These differences turn out to be positive and significant only for specific industries and types of educational levels, which is logical in terms of the abovementioned industry specificities.

Spatially lagged human-capital variables that measure lower levels of human capital (W_INCOMPE and W_PRIMEDU) have a positive and significant effect on the location of new plants in industries with low-medium technological levels, such as natural-resource-intensive, labour-intensive, differentiated-products and scale-economy-intensive industries. The explanation is that whereas firms from these industries use low-skilled labour (albeit with different intensities), firms from R&D-intensive industries do not rely on employees of this type. Additionally, medium levels of education (W_MIDSCH, W_TECHS1, W_TECHS2 and W_HIGHS) are very important to manufacturing firms,

[18] For a discussion of which spatial levels should be used when analysing the location decisions of new plants, see Arauzo-Carod and Manjón-Antolín (2011) and Arauzo-Carod (2008).

regardless of technological level, because the skills provided by employees with these educational attainments are useful for a wide range of activities and industries. Higher educational levels (W_MEDUNI and W_HIGHUNI) also show interesting results: firms from low-tech industries are positively influenced by the presence of individuals with intermediate university degrees (W_MEDUNI) and advanced university degrees (W_HIGHUNI); firms from industries of a medium technological level show a similar pattern, but with advanced university degrees (W_HIGHUNI) playing a less important role; and finally, high-tech firms are positively influenced only by the presence of individuals with advanced university degrees (W_HIGHUNI).

These results help to illustrate how the location decisions of manufacturing firms are shaped by the characteristics of potential sites in terms of educational attainments, but the variables used in the econometric estimations obviously do not explain the whole decision process, in view of the fact that *i)* some variables could be omitted (for instance, some characteristics of entrepreneurs such as where they live, family characteristics or specific linkages to specific areas), and *ii)* there are some random processes that affect these decisions. This implies, for instance, that some municipalities deemed (a priori) to be unsuitable (due to their characteristics and the characteristics of the entering firms) could in fact be chosen.

5. Conclusions

In this paper, we have tried to empirically asses the influence of the skill level of individuals on the location decisions of manufacturing firms, an issue that has received little attention from scholars. Our results show that *i)* firms do not perceive educational attainments strictly at the local level, but rather at a broader level, and *ii)* depending on a firm's characteristics (i.e., industry) the educational attainments of the individuals in a specific area may play different roles in plant location decisions. Therefore, there are both geographical and industry-specific dimensions to be considered in firm location processes. Our empirical findings also suggest that a failure to take spatial issues and industry-specific effects into account could lead to biased results.

Nevertheless, our findings should be considered cautiously. In this paper, we have approached skill levels only in terms of formal education, but some firms prefer to train or retrain workers (Woodward, 1992), and formal educational levels would not be very important in such circumstances because the firms could upgrade them.

Some interesting and useful policy implications arise from our results: firstly, firms take human-capital stock into account in their decisions, but at the local level, so educational policies should focus on areas larger than local units; secondly, firms from different industries differ in their educational requirements, so public policies should take into account regional specialisation levels in order to better design public educational programmes; and thirdly, although firms rely mainly on specific educational levels according to their characteristics, access to certain types of educational levels is useful for firms of all sorts, regardless of location (and as a result, transport infrastructures are relevant).

As this is a first attempt to explore the role played by educational attainments on firm location decisions, there is still room for new contributions. Future research should attempt to better identify firms' demands in terms of educational attainments in order to better match such requirements with geographical stock of human capital. An alternative way of identifying these demands could be to take into account the technological level of both the firms and their products instead of just considering the industries to which firms belong.

References

Alamá-Sabater, L.; Artal-Tur, A. and Navarro-Azorín, J.M. (2011): "Industrial location, spatial discrete choice models and the need to account for neighbourhood effects", *The Annals of Regional Science*, forthcoming.

Alañón, Á.; Arauzo-Carod, J.M. and Myro, R. (2007): "Accessibility, agglomeration and location," in J.M. Arauzo-Carod and M. Manjón-Antolín (eds.), *Entrepreneurship, Industrial Location and Economic Growth*, Chentelham: Edward Elgar, pp. 247-267.

Arauzo-Carod, J.M. (2009): "Location determinants of high-tech manufacturing activities: a preliminary analysis", *Letters in Spatial and Resource Sciences* **2(1)**: 23-29.

Arauzo-Carod, J.M. (2008): "Industrial Location at a Local Level: Comments on the Territorial Level of the Analysis," *Tijdschrift voor Economische en Sociale Geografie - Journal of Economic & Social Geography* **99**, 193-208.

Arauzo-Carod, J.M. (2005): "Determinants of Industrial Location. An Application for Catalan Municipalities", *Papers in Regional Science* **84**: 105-120.

Arauzo-Carod, J.M.; Liviano-Solis, D. and Manjón-Antolín, M. (2010): "Empirical Studies in Industrial Location: An Assessment of their Methods and Results", *Journal of Regional Science* **50 (3)**: 685-711.

Arauzo-Carod, J.M. and Manjón-Antolín, M. (2011): "(Optimal) Spatial Aggregation in the Determinants of Industrial Location", *Small Business Economics*, forthcoming.

Arauzo-Carod, J.M. and Manjón-Antolín, M. (2004): “Firm Size and Geographical Aggregation: An Empirical Appraisal in Industrial Location”, *Small Business Economics* **22**: 299-312.

Arauzo-Carod, J.M. and Viladecans, E. (2009): “Industrial Location at the Intrametropolitan Level: The Role of Agglomeration Economies”, *Regional Studies* **43 (4)**: 545-558.

Audretsch, D. and Lehmann, E. (2005): “Does the Knowledge Spillover Theory of Entrepreneurship hold for regions?”, *Research Policy* **34**: 1191-1202.

Bartik, T.J. (1985): “Business Location Decisions in the U.S.: Estimates of the Effects of Unionization, Taxes, and Other Characteristics of States”, *Journal of Business and Economic Statistics* **3**: 14-22.

Bartik, T.J. (1988): “The Effects of Environmental Regulation on Business Location in the United States”, *Growth and Change* **19**: 22–44.

Cameron, A.C. and Trivedi, P.K (1998): *Regression Analysis of Count Data*, Cambridge: Cambridge University Press.

Cheng, S. and Stough, R. (2006): “Location decisions of Japanese new manufacturing plants in China: a discrete-choice analysis”, *The Annals of Regional Science* **43**: 369-387.

Cieślik, A. (2005): “Location of foreign firms and national border effects: the case of Poland” *Tijdschrift voor Economische en Sociale Geografie - Journal of Economic & Social Geography* **96**: 287-297.

Coughlin, C.C. and Segev, E. (2000): “Location determinants of new foreign-owned manufacturing plants”, *Journal of Regional Science* **40**: 323-351.

Egeln, J.; Gottschalk, S. and Rammer, C. (2004): “Location Decisions of Spin-offs from Public Research Institutions” *Industry and Innovation* **11**: 207-223.

Gabe, T. and Bell, K.P. (2004): "Tradeoffs Between Local Taxes and Government Spending as Determinants of Business Location", *Journal of Regional Science* **44 (1)**: 21-41.

Gabe, T. (2003): “Local Industry Agglomeration and New Business Activity” *Growth and Change* **34(1)**: 17–39.

Guimarães, P.; Figueiredo, O. and Woodward, D. (2000): “Agglomeration and the Location of Foreign Direct Investment in Portugal”, *Journal of Urban Economics* **47**: 115-135.

Hansen, E.R. (1987): “Industrial location choice in São Paulo, Brazil: A nested logit model”, *Regional Science and Urban Economics* **17**: 89–108.

Holl, A. (2004a): “Start-ups and Relocations: Manufacturing Plant Location in Portugal”, *Papers in Regional Science* **83**: 649-668.

Holl, A. (2004b): “Transport Infrastructure, Agglomeration Economies, and Firm Birth. Empirical Evidence from Portugal”, *Journal of Regional Science* **44**: 693-712.

Holl, A. (2004c): “Manufacturing location and impacts of road transport infrastructure: Empirical evidence from Spain”, *Regional Science and Urban Economics* **34**: 341-363.

Kim, H.; Waddell, P.; Shankar, V.N. and Ulfarsson, G.F. (2008): “Modelling Micro-Spatial Employment Location Patterns: A Comparison of Count and Choice Approaches”, *Geographical Analysis* **40**: 123-151.

Luger, M.I. and Shetty, S. (1985): “Determinants of Foreign Plant Start-ups in the United States: Lessons for Policymakers in the Southeast”, *Vanderbilt Journal of Transnational Law* **18**: 223-245.

Manjón-Antolín, M. and Arauzo-Carod, J.M. (2011): “Locations and relocations: determinants, modelling, and interrelations”, *The Annals of Regional Science*, forthcoming.

Moran, P. (1948): “The interpretation of statistical maps”, *Journal of the Royal Statistical Society* **59**: 185-193.

Schmenner, R.W.; Huber, J.C. and Cook, R.L. (1987): ”Geographic differences and the location of new manufacturing facilities”, *Journal of Urban Economics* **21**: 83–104.

Smith, D.F. and Florida, R. (1994): “Agglomeration and Industrial Location: An Econometric Analysis of Japanese-Affiliated Manufacturing Establishments in Automotive-Related Industries”, *Journal of Urban Economics* **36**: 23-41.

Trullén, J. and Boix, R. (2005): *Indicadors 2005*, Diputació de Barcelona i Universitat Autònoma de Barcelona.

Woodward, D. (1992): “Locational determinants of Japanese manufacturing start-ups in the United States”, *Southern Economic Journal* **58**: 690–708.

Tables

Table 1. Descriptive statistics about human capital

HC variable	Mean	Std. dev.	Min.	Max.	Mean by municipality size*		
					Small	Medium	Big
ILLI	0.451	0.638	0	6.863	0.366	0.629	0.727
INCOMPE	3.392	3.438	0	31.250	3.071	4.016	4.968
PRIMEDU	17.141	7.921	0	49.758	16.954	17.653	16.107
MIDSCH	34.750	9.173	8.333	75.380	35.079	34.351	29.933
TECHS1	7.849	3.179	0	24.638	7.814	7.921	7.971
TECHS2	7.923	3.351	0	31.818	8.012	7.679	8.407
HIGHS	12.156	4.798	1.626	40.351	12.217	11.969	12.739
MEDUNI	8.466	3.305	0	25.000	8.563	8.202	9.001
HIGHUNI	7.870	4.163	0	34.783	7.922	7.579	10.147
YEARS	8.500	1.012	4.236	11.994	8.467	8.570	8.643

*Municipality sizes are as follows: small (0-2,000 inhabitants), medium (2,001-50,000 inhabitants) and big (more than 50,000 inhabitants)
Source: Authors' calculations.

Table 2. Correlation table: human-capital variables

	ILLI	INCOMPE	PRIMEDU	MIDSCH	TECHS1	TECHS2	HIGHS	MEDUNI	HIGHUNI	YEARS
ILLI	1.000									
INCOMPE	0.1814	1.000								
PRIMEDU	0.0237	0.1821	1.000							
MIDSCH	-0.0030	-0.2614	-0.4053	1.000						
TECHS1	-0.0773	-0.1121	-0.0513	-0.1650	1.000					
TECHS2	-0.0949	-0.1870	-0.1979	-0.2445	0.2011	1.000				
HIGHS	-0.0257	-0.0854	-0.3476	-0.2285	-0.2251	-0.1142	1.000			
MEDUNI	-0.1621	-0.2438	-0.2729	-0.3338	0.0259	0.2023	0.1299	1.000		
HIGHUNI	-0.0478	-0.0958	-0.3480	-0.3648	-0.1211	0.0967	0.2476	0.3547	1.000	
YEARS	-0.0717	-0.4759	-0.7236	0.1370	-0.0497	0.2097	0.4042	0.4536	0.5223	1.000

Source: Authors' calculations.

Table 3. Descriptive statistics about entrants

Industry	Mean	Std. dev.	Min.	Max.	% of zeros
12 Mining of uranium and thorium ores	-	-	-	-	-
13 Mining of metal ores	-	-	-	-	-
14 Mining of non-ferrous metal ores	0.011	0.102	0	1	0.99
15 Manufacture of food products and beverages	0.281	1.464	0	33	0.87
16 Manufacture of tobacco products	0.001	0.033	0	1	0.99
17 Manufacture of textiles	0.254	1.843	0	43	0.91
18 Manufacture of leather clothes	0.298	3.768	0	110	0.93
19 Tanning and dressing of leather	0.013	0.129	0	2	0.99
20 Manufacture of wood and of wood and cork products, except furniture	0.325	0.892	0	9	0.81
21 Manufacture of pulp, paper and paper products	0.085	0.408	0	6	0.94
22 Publishing, printing and reproduction of recorded media	0.238	1.581	0	38	0.91
23 Manufacture of coke, refined petroleum products and nuclear fuel	0.001	0.033	0	1	0.99
24 Manufacture of chemicals and chemical products	0.131	0.495	0	7	0.90
25 Manufacture of rubber and plastic products	0.181	0.719	0	8	0.90
26 Manufacture of other non-metallic mineral products	0.180	0.583	0	7	0.88
27 Manufacture of basic metals	0.036	0.208	0	3	0.97
28 Manufacture of fabricated metal products, except machinery and equipment	1.308	4.119	0	55	0.67
29 Manufacture of machinery and equipment n.e.c.	0.475	1.579	0	20	0.81
30 Manufacture of office machinery and computers	0.002	0.046	0	1	0.99
31 Manufacture of electrical machinery and apparatus n.e.c.	0.124	0.554	0	9	0.92
32 Manufacture of radio, television and communication equipment	0.046	0.310	0	5	0.97
33 Manufacture of medical, precision and optical instruments, watches and clocks	0.063	0.556	0	15	0.96
34 Manufacture of motor vehicles, trailers and semi-trailers	0.119	0.546	0	8	0.92
35 Manufacture of other transport equipment	0.039	0.251	0	4	0.97
36 Manufacture of furniture; manufacturing n.e.c.	0.318	1.705	0	43	0.86

Source: Authors' calculations.

Table 4. Estimation tests

Model	AIC	LOG	Vuong test
Poisson	7330.489	-3648.2444	-
Negative binomial	3413.774	-1688.887	-
Zero-inflated Poisson	6001.86	-2981.93	6.58***
Zero-inflated negative binomial	3245.365	-1602.683	6.88***

Source: Authors' calculations.

Table 5. Spatial autocorrelation of human-capital values

HC variable	Moran's I	P-value
ILLI	0.0318	0.0010
INCOMPE	0.0095	0.0040
PRIMEDU	0.0349	0.0010
MIDSCH	0.0595	0.0010
TECHS1	0.0420	0.0010
TECHS2	0.0574	0.0010
HIGHS	0.0950	0.0010
MEDUNI	0.0170	0.0010
HIGHUNI	0.0400	0.0010
YEARS	0.0890	0.0010

Source: Authors' calculations.

Table 6. Estimation without industry effects (zero-inflated negative binomial)

	Without spatial effects	With spatial effects
INCOMPE	-0.0791	0.000775
	(0.149)	(0.128)
PRIMEDU	-0.144	-0.0380
	(0.141)	(0.121)
MIDSCH	-0.175	-0.0566
	(0.140)	(0.121)
TECHS1	-0.108	-0.0183
	(0.143)	(0.124)
TECHS2	-0.184	-0.0854
	(0.141)	(0.123)
HIGHS	-0.112	-0.0400
	(0.142)	(0.123)
MEDUNI	-0.187	-0.0778
	(0.143)	(0.124)
HIGHUNI	-0.185	-0.112
	(0.141)	(0.123)
YEARS	0.339**	0.212
	(0.151)	(0.153)
DENS	0.000195***	7.06e-05**
	(4.04e-05)	(3.06e-05)
CAP	1.351***	1.755***
	(0.192)	(0.182)
COAST	0.384**	0.548***
	(0.179)	(0.181)
PROVCAP	-1.33e-05***	-1.90e-05***
	(2.39e-06)	(3.00e-06)
CI	0.121	0.173**
	(0.0935)	(0.0851)
SMALL	-0.0115***	-0.00977***
	(0.00300)	(0.00275)
JOB_IND	4.587***	0.695
	(0.749)	(0.786)
W_INCOMPE		6.036***
		-1.519
W_PRIMEDU		5.702***
		-1.308
W_MIDSCH		5.176***
		-1.296
W_TECHS1		6.553***
		-1.346
W_TECHS2		4.857***
		-1.375
W_HIGHS		5.520***
		-1.307
W_MEDUNI		4.583***

		-1.104
W_HIGHUNI		4.439***
		-1.311
W_YEARS		5.734***
		-1.227
Constant	13.72	-572.5***
	(14.02)	(133.6)
Inflated variables		
POPULATION	-0.00327***	-0.00343***
	(0.000644)	(0.000813)
Constant	1.890***	1.921***
	(0.297)	(0.339)
Lnalpha	0.0295	-0.234**
	(0.0882)	(0.0982)
Observations	946	946
Log Lik	-1602.683	-1550.468

Source: Authors' calculations. Standard errors in brackets.

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

Table 7. Estimation with industry effects and spatial effects using OECD classification (zero-inflated negative binomial)

	E_NAT Without spatial effects	E_NAT With spatial effects	E_LAB Without spatial effects	E_LAB With spatial effects	E_DIF Without spatial effects	E_DIF With spatial effects	E_R&D Without spatial effects	E_R&D With spatial effects	E_SCA Without spatial effects	E_SCA With spatial effects
INCOMPE	0.111	0.0954	-0.162	-0.0954	0.0180	0.0574	0.436	0.231	-0.127	-0.168
	(0.239)	(0.219)	(0.210)	(0.174)	(0.163)	(0.143)	(0.462)	(0.480)	(0.217)	(0.212)
PRIMEDU	0.0550	0.0751	-0.217	-0.116	-0.0886	-0.00596	0.483	0.275	-0.207	-0.214
	(0.220)	(0.204)	(0.197)	(0.166)	(0.150)	(0.132)	(0.421)	(0.439)	(0.204)	(0.194)
MIDSCH	0.0573	0.0808	-0.230	-0.121	-0.106	-0.0140	0.506	0.284	-0.228	-0.236
	(0.220)	(0.205)	(0.196)	(0.166)	(0.149)	(0.133)	(0.418)	(0.434)	(0.202)	(0.193)
TECHS1	0.145	0.136	-0.170	-0.0869	-0.0493	0.0141	0.534	0.307	-0.251	-0.288
	(0.228)	(0.212)	(0.199)	(0.169)	(0.153)	(0.136)	(0.438)	(0.446)	(0.209)	(0.201)
TECHS2	0.0739	0.0662	-0.202	-0.114	-0.115	-0.0449	0.455	0.199	-0.186	-0.179
	(0.219)	(0.206)	(0.193)	(0.165)	(0.151)	(0.135)	(0.417)	(0.432)	(0.200)	(0.193)
HIGHS	0.139	0.122	-0.151	-0.0912	-0.0224	0.0186	0.704*	0.310	-0.175	-0.246
	(0.222)	(0.205)	(0.197)	(0.167)	(0.152)	(0.134)	(0.401)	(0.425)	(0.201)	(0.193)
MEDUNI	0.0993	0.103	-0.226	-0.129	-0.113	-0.0293	0.664	0.242	-0.248	-0.253
	(0.226)	(0.211)	(0.203)	(0.174)	(0.151)	(0.135)	(0.439)	(0.448)	(0.210)	(0.201)
HIGHUNI	0.0694	0.0540	-0.168	-0.111	-0.154	-0.0989	0.612	0.323	-0.199	-0.258
	(0.223)	(0.207)	(0.195)	(0.166)	(0.153)	(0.136)	(0.435)	(0.441)	(0.206)	(0.197)
YEARS	-0.323	-0.299	-0.156	-0.223	0.385**	0.233	-1.286*	-0.267	0.0600	0.0717
	(0.288)	(0.278)	(0.226)	(0.216)	(0.175)	(0.179)	(0.663)	(0.609)	(0.288)	(0.285)
DENS	8.47e-05**	3.30e-05	0.000196***	8.59e-05***	0.000152***	5.05e-05*	4.46e-05	3.40e-05	4.70e-05	-1.50e-05
	(3.60e-05)	(3.40e-05)	(4.47e-05)	(3.33e-05)	(3.55e-05)	(2.98e-05)	(3.40e-05)	(3.51e-05)	(3.24e-05)	(3.12e-05)
CAP	1.473***	1.806***	1.168***	1.664***	1.298***	1.660***	0.138	0.605*	0.720***	1.080***
	(0.256)	(0.267)	(0.222)	(0.218)	(0.199)	(0.192)	(0.340)	(0.367)	(0.234)	(0.242)
COAST	0.932***	1.013***	0.588***	0.614***	0.0783	0.217	0.854***	0.551	-0.0772	0.0451
	(0.267)	(0.281)	(0.225)	(0.231)	(0.191)	(0.194)	(0.314)	(0.385)	(0.247)	(0.254)
PROVCAP	-1.59e-05***	-2.19e-05***	-9.99e-07	-6.60e-06	-1.88e-05***	-2.30e-05***	-2.21e-05**	-3.96e-05***	-1.58e-05***	-1.93e-05***
	(4.56e-06)	(5.62e-06)	(3.28e-06)	(4.27e-06)	(2.88e-06)	(3.56e-06)	(1.03e-05)	(1.51e-05)	(4.40e-06)	(5.75e-06)
CI	0.0559	0.113	0.0432	0.116	0.158	0.202**	-0.568	-0.384	0.0264	0.0860
	(0.165)	(0.156)	(0.123)	(0.114)	(0.111)	(0.103)	(0.367)	(0.337)	(0.160)	(0.152)
SMALL	-0.00772	-0.00680	-0.00416	-0.00409	-0.0107***	-0.00936***	-0.0221**	-0.0173*	-0.0164***	-0.0172***
	(0.00500)	(0.00476)	(0.00405)	(0.00373)	(0.00338)	(0.00316)	(0.00944)	(0.00923)	(0.00443)	(0.00435)
JOB_IND	4.412***	1.666	5.782***	1.500	3.813***	-0.0757	10.62***	2.598	2.939**	-1.465
	-1.330	-1.389	-1.003	-1.048	(0.860)	(0.952)	-3.396	-3.580	-1.266	-1.424
W_INCOMPE		7.571**		7.554***		4.241**		7.786		5.192*

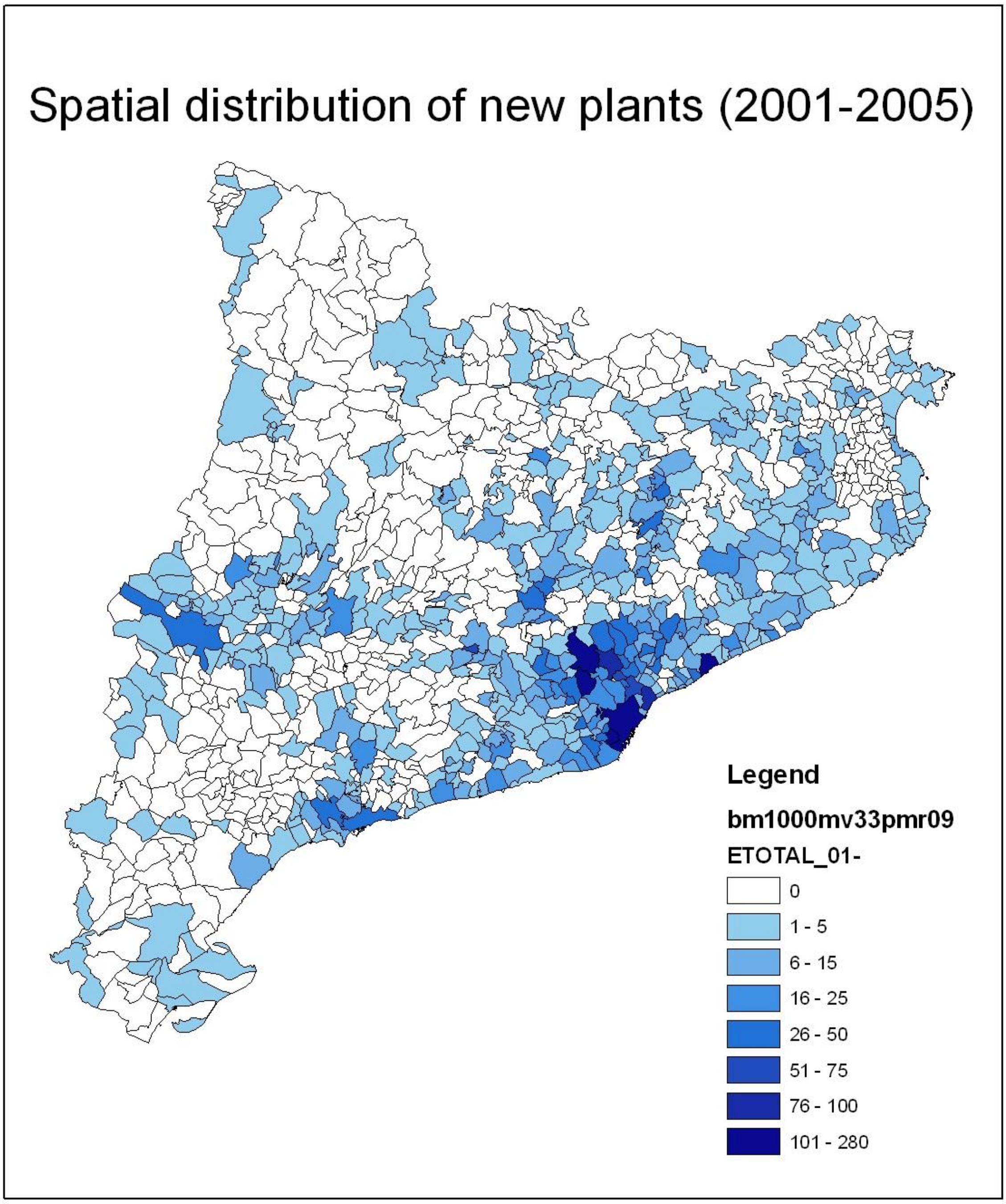
		-3.058		-2.154		-1.783		-6.966		-2.753
W_PRIMEDU		6.728***		7.073***		4.050***		9.492		5.218**
		-2.570		-1.847		-1.524		-5.804		-2.347
W_MIDSCH		6.106**		6.598***		3.518**		9.848*		5.072**
		-2.547		-1.818		-1.503		-5.663		-2.319
W_TECHS1		8.106***		8.251***		4.741***		13.17**		7.215***
		-2.460		-1.852		-1.534		-5.341		-2.317
W_TECHS2		5.844**		6.346***		3.275**		8.545		4.397*
		-2.854		-1.950		-1.622		-6.459		-2.527
W_HIGHS		6.469**		6.546***		3.928**		10.95*		5.703**
		-2.577		-1.834		-1.525		-5.747		-2.367
W_MEDUNI		4.591**		5.776***		3.453***		5.666		3.503*
		-2.270		-1.594		-1.311		-5.253		-2.012
W_HIGHUNI		5.137**		6.003***		2.666*		9.798*		3.582
		-2.467		-1.849		-1.505		-5.662		-2.361
W_YEARS		7.094***		7.562***		5.243***		-1.805		5.858***
		-2.458		-1.728		-1.444		-5.930		-2.188
Constant	-6.535	-688.7***	20.27	-719.2***	6.518	-410.9***	-43.89	-972.7*	21.20	-528.1**
	(22.06)	(263.3)	(19.54)	(187.4)	(14.89)	(155.3)	(41.55)	(590.9)	(20.32)	(237.9)
Inflated variables										
POPULATION	-0.00190**	-0.00274*	-0.00205***	-0.00229***	-0.00208***	-0.00206***	-0.000154***	-0.000156**	-0.00137***	-0.00154***
	(0.000826)	(0.00159)	(0.000487)	(0.000736)	(0.000397)	(0.000411)	(4.81e-05)	(6.66e-05)	(0.000451)	(0.000516)
Constant	2.132***	2.161***	2.068***	1.939***	1.958***	1.918***	2.899***	2.214***	2.638***	2.692***
	(0.540)	(0.721)	(0.334)	(0.403)	(0.276)	(0.280)	(0.453)	(0.594)	(0.442)	(0.474)
Lnalpha	-0.0213	-0.367	0.136	-0.228	-0.0713	-0.342***	-15.05	-16.80	-0.291	-0.619**
	(0.217)	(0.249)	(0.124)	(0.143)	(0.109)	(0.121)	(681.7)	(769.7)	(0.220)	(0.253)
Observations	946	946	946	946	946	946	946	946	946	946
Log Lik	-503.6	-479.5	-886.5	-843.7	-1207	-1171	-169.0	-154.9	-558.5	-539.4

Source: Authors' calculations. Standard errors in brackets. OECD classification: E_NAT (natural-resource-intensive sectors), E_LAB (labour-intensive sectors), E_DIF (sectors with differentiated products), E_R&D (R&D-intensive sectors) and E_SCA (scale-economy-intensive sectors).

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

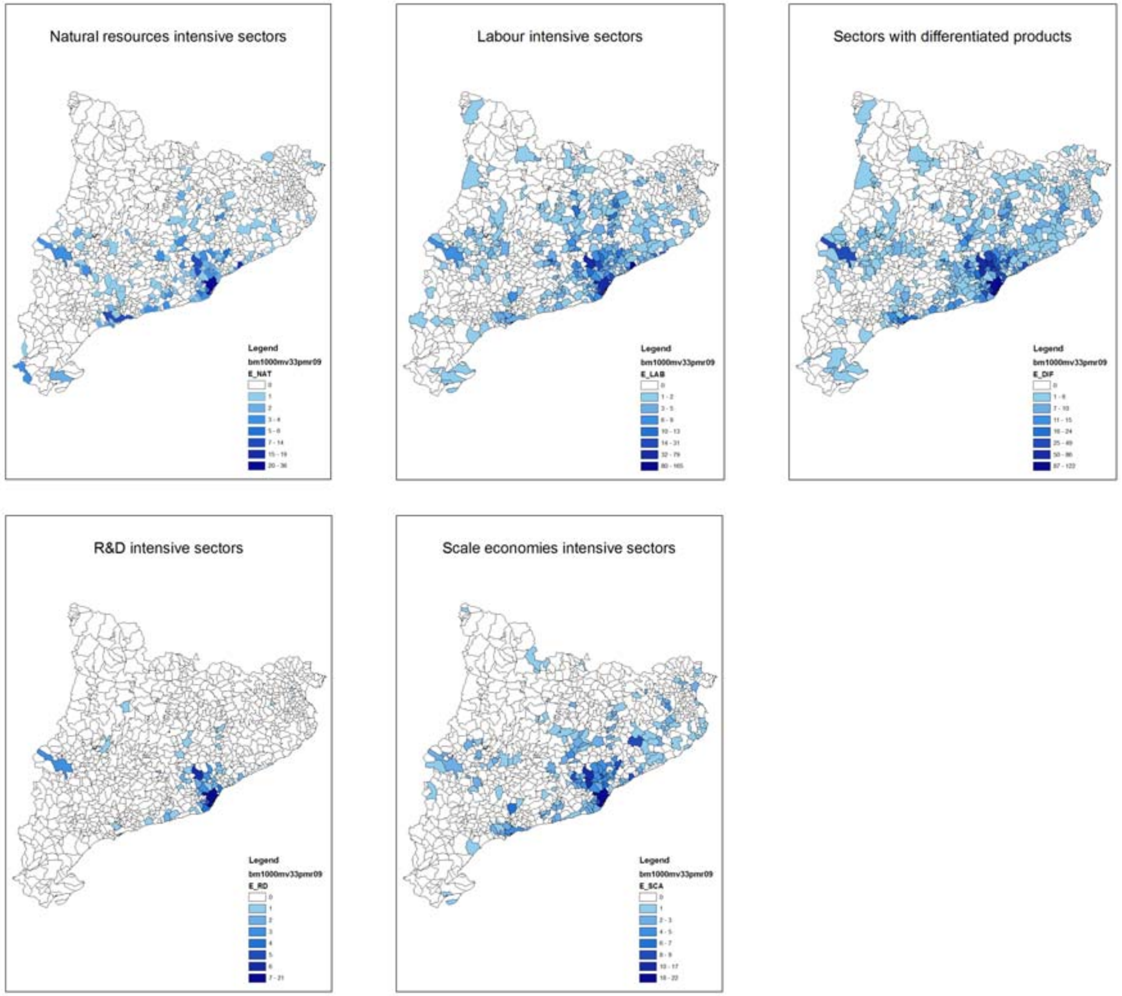
Figures

Figure 1. Spatial distribution of new plants (2001-2005)



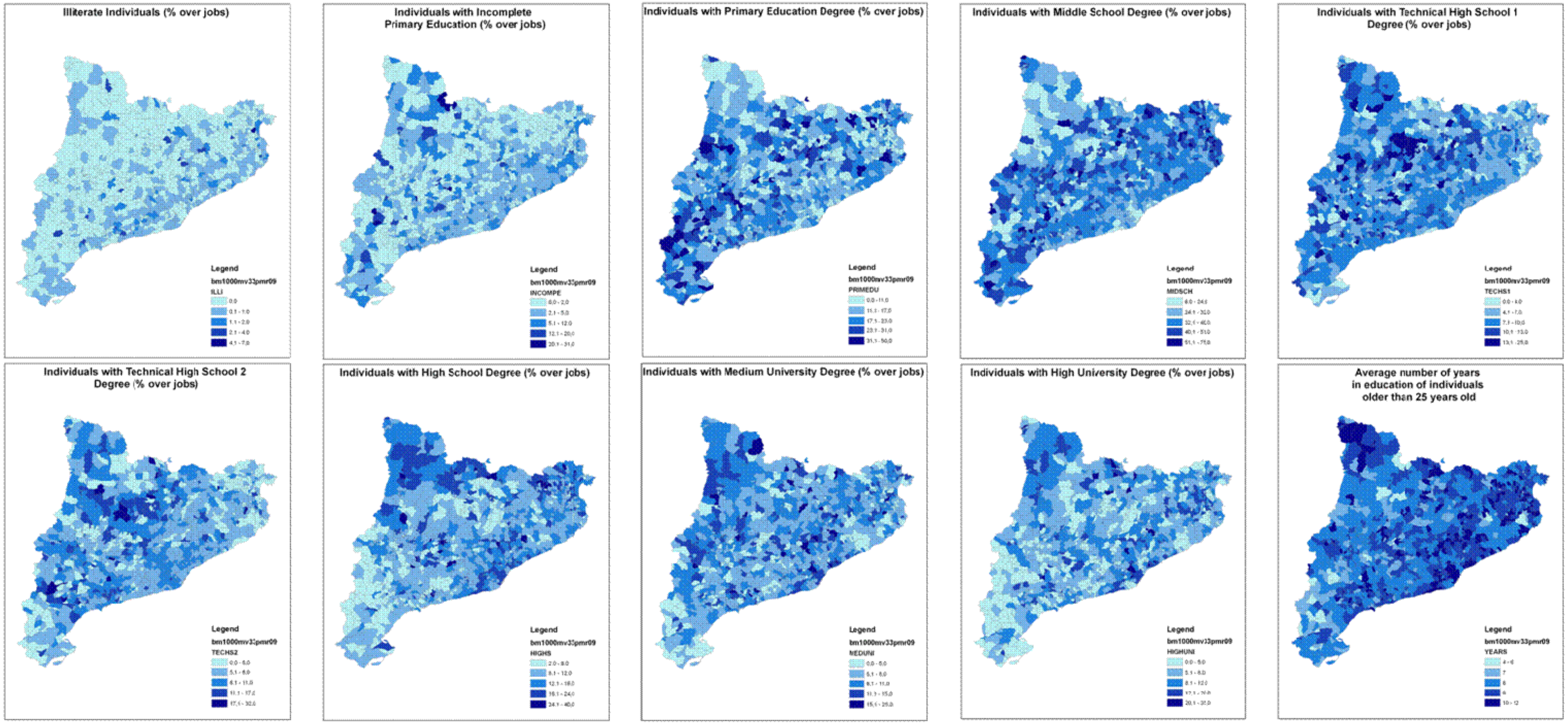
Source: Authors' calculations with data from the REIC.

Figure 2. Spatial distribution of new plants (2001-2005) by OECD industry



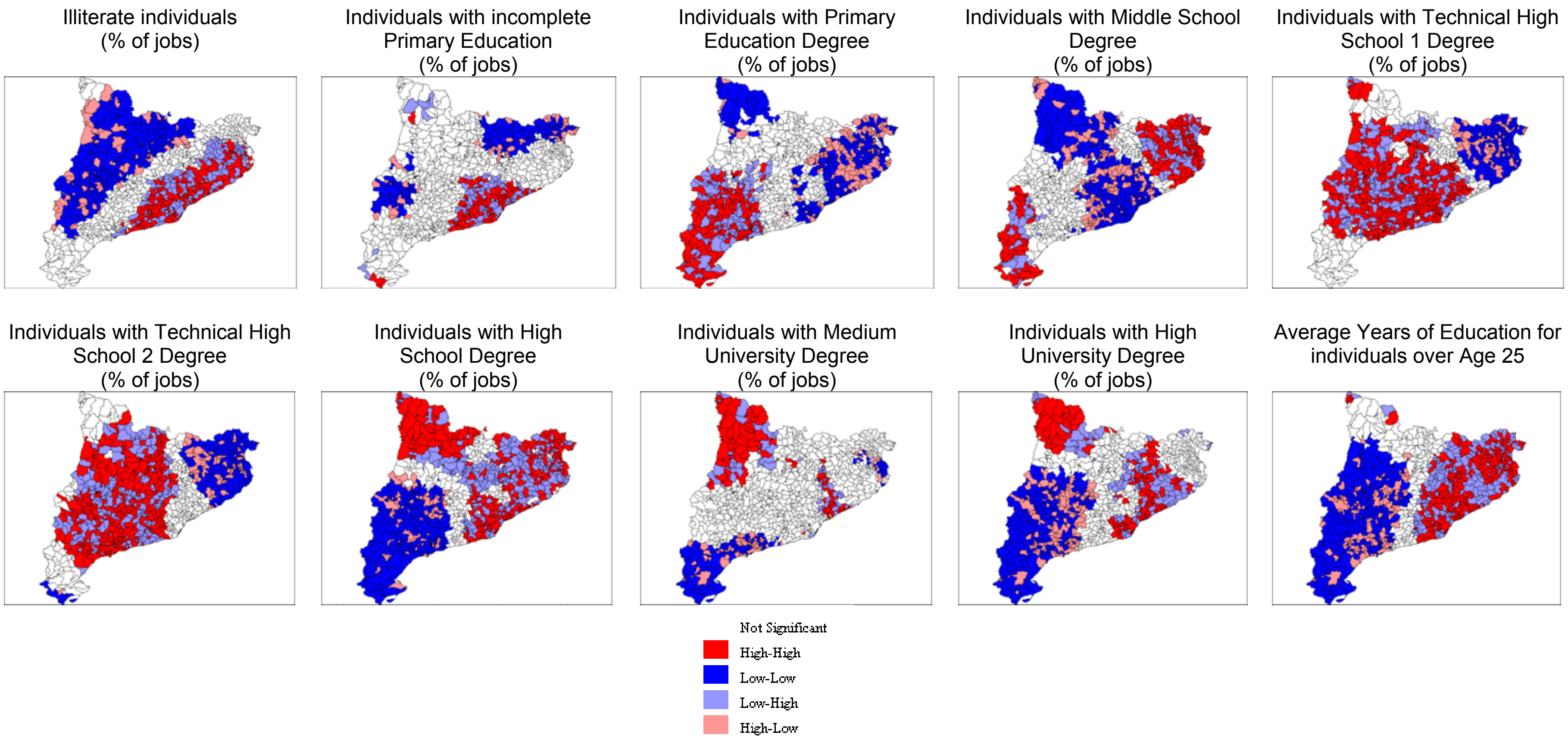
Source: Authors' calculations with data from the REIC.

Figure 3. Descriptive statistics about human capital



Source: Authors' calculations with data from the REIC.

Figure 4. Local Index of Spatial Association (LISA) of human-capital variables



Source: Authors' calculations with data from the REIC.

Appendices

Table A.1. Mean annual income by educational level in Catalonia (2002)

Education	Mean annual income (€)	Mean annual income (index)
Without	13,770.4	100
Primary	16,443.8	119
Secondary	19,073.7	139
Technical	20,779.0	151
University	29,728.0	216
Mean income	*20,728.6*	*151*

Source: IDESCAT

Table A.2. Industry classifications

Two-digit level	OECD classification
12 Mining of uranium and thorium ores	Natural-resource-intensive sectors
13 Mining of metal ores	Natural-resource-intensive sectors
14 Mining of non-ferrous metal ores	Natural-resource-intensive sectors
15 Manufacture of food products and beverages	Natural-resource-intensive sectors
16 Manufacture of tobacco products	Natural-resource-intensive sectors
17 Manufacture of textiles	Labour-intensive sectors
18 Manufacture of leather clothes	Labour-intensive sectors
19 Tanning and dressing of leather	Labour-intensive sectors
20 Manufacture of wood and of wood and cork products, except furniture	Labour-intensive sectors
21 Manufacture of pulp, paper and paper products	Natural-resource-intensive sectors
22 Publishing, printing and reproduction of recorded media	Sectors with differentiated products
23 Manufacture of coke, refined petroleum products and nuclear fuel	Natural-resource-intensive sectors
24 Manufacture of chemicals and chemical products	Scale-economy-intensive sectors
25 Manufacture of rubber and plastic products	Scale-economy-intensive sectors
26 Manufacture of other non-metallic mineral products	Sectors with differentiated products
27 Manufacture of basic metals	Sectors with differentiated products
28 Manufacture of fabricated metal products, except machinery and equipment	Sectors with differentiated products
29 Manufacture of machinery and equipment n.e.c.	Sectors with differentiated products
30 Manufacture of office machinery and computers	R&D-intensive sectors
31 Manufacture of electrical machinery and apparatus n.e.c.	Sectors with differentiated products
32 Manufacture of radio, television and communication equipment	R&D-intensive sectors
33 Manufacture of medical, precision and optical instruments, watches and clocks	R&D-intensive sectors
34 Manufacture of motor vehicles, trailers and semi-trailers	Scale-economy-intensive sectors
35 Manufacture of other transport equipment	Scale-economy-intensive sectors
36 Manufacture of furniture; manufacturing n.e.c.	Labour-intensive sectors

Source: IDESCAT, OECD (2001). Drawn up by the authors.