UNIVERSITAT ROVIRA I VIRGILI

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Productivity and human capital: a business-level analysis.

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Document de treball nº -31- 2010

DEPARTAMENT D'ECONOMIA
Facultat de Ciències Econòmiques i Empresarials

Edita:

Departament d'Economia
http://www.fcee.urv.es/departaments/economia/public_html/index.html
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Dirigir comentaris al Departament d'Economia.

Dipòsit Legal: T - 2027 - 2010

ISSN 1988 - 0812

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Productivity and human capital: a business-level analysis

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This paper aims to analyse the impact of human capital on business productivity, focusing the analysis on the possible effect of the complementarity that exists between human capital and new production technologies, particularly advanced manufacturing technologies (AMTs) for the specific case of small and medium enterprises (SMEs) in Catalonia. Additionally, following the theory of skill-biased technological change, the paper analyses whether technological change produces bias exclusively in the skills required for managers, or whether the bias extends to the skills required of production staff. With this objective, we have compared the possible existence of complementarity between AMTs and the level of human capital for different occupational groups. The results confirm the complementary relationship between human capital and new production technologies. The results by occupational group confirm that to maximise the productivity of new technologies, skilled staff are needed both in management and production, with managers and professionals as well as skilled operatives playing a vital role.

Keywords: human capital, process technologies, complementarity, business productivity

(JEL D24, J24, O30)

1. Introduction

In recent years the Spanish and Catalan economies have invested heavily in human capital and new technologies with the aim of improving business competitiveness. Unfortunately, despite the efforts made, productivity growth remains small compared to in other European Union (EU) countries.

The data confirm that the overall growth of the Catalan and Spanish economies, measured in "gross value-added (GVA)", is higher than in other euro-zone countries. In 2000-2004, for instance, the annual GVA growth rate was 2.78% in Catalonia and 2.89% in Spain as a whole, both of which were above the overall rate of 1.5% for the EU (EU-15) during the same period. But this growth was primarily due to a higher rate of employment rather than improved business efficiency. So, while employment growth over the same period stood at 2.46% in Spain and 0.44% in the EU-15 countries, labour productivity growth in Spain (0.43%) was below the EU-15 rate (1.07%). In Catalonia, growth in employment stood at 2.4% for 1995-2003, while the year-on-year increase in labour productivity was a meagre 0.5% (or just 0.45% for 2000-2003) (Mas and Quesada, 2007; Oliver, 2009).

Given that growth in business productivity is strongly linked to improved living standards of the population, it is not surprising that economic agents are striving to find mechanisms to increase business productivity. This is especially true in Catalonia and Spain, where data confirm that apparent labour productivity stagnated for 2001-2006 (Amarelo, 2007).

We must therefore ask why the Spanish and Catalan economies are still not seeing improvements in productivity, despite investment in education[1]. One explanation could be the region's production structure, which is heavily weighted towards traditional, labour-intensive sectors whose productivity is relatively low compared to that of technology-intensive sectors. Another possible explanation, which goes beyond the country's structural conditions, is that Spanish and Catalan businesses are not using available technological and human resources efficiently to improve productivity[2].

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[1] Spain has undergone a major transformation in job skills. In 1985, 63.3% of the Spanish population only had primary-school qualifications, and 12% had no qualifications. Seventeen years later, in 2002, these figures had fallen to 18.4% and 3.6% respectively. But the most radical change has taken place in secondary education, where the ratio increased from 26.5% in 1985 to 57.2% in 2002. The percentage of employees with university qualifications increased from 4.9% to 11.5% (Mas and Quesada, 2005).

[2] Another possible explanation is that new technologies do not really affect business productivity (Solow's "productivity paradox" [1987]). In this respect, the first company-level works to analyse the relationship between investment in new technologies and business productivity (1980s and 1990s) found no evidence for this relationship, which contributed to broadening the debate on the productivity paradox. Today, the emergence of new studies, especially since the 1990s, shows that these new technologies do indeed contribute to productivity growth, thus putting an end to the debate surrounding the productivity paradox. These studies propose various explanations for the lack of evidence of a relationship between new technologies and business productivity in the early studies. These include the sample size, the quality of the data, the analysis methodology, the fact that the effects do not occur in the short term but

This paper presents an in-depth study of the effect of human capital on the productivity of Catalan businesses and an analysis of the impact of new technologies on both business productivity and human capital productivity. It is essential to recognise the scope of these effects to assess the improvement in the competitiveness of businesses and thus identify their strengths and weaknesses. Moreover, as Huerta (2003) underlines, the uncertainty of the impact of human capital can sometimes lead to the development of approaches in which investment in technologies is presented as the only valuable dimension of business transformation and the importance of human capital as a determining factor in business productivity is ignored.

In this regard, while knowledge of Spanish companies is steadily increasing and many studies have been carried out into company decisions on R&D, internalisation, diversification and pricing and into the effects of technologies, size and innovation activities on productivity, almost no studies have directly analysed the relationship between human capital and business productivity. This is largely because it is difficult to find databases that combine information on the characteristics of companies with information on the characteristics of workers. This problem is not limited to Catalonia. Analysis of global evidence shows that on the one hand company-level studies are a recent phenomenon, and on the other, very few works have successfully analysed the effects of human capital on business productivity due to the lack of available data[3].

Therefore, although the database used in this study is a cross-section, it presents a number of advantages that should not be neglected. First, unlike the vast majority of jobs, company and employee data were compiled using a single company survey, thus avoiding the problems associated with merging distinct databases. Second, because we had company and employee information we were able to carry out this pioneer type of analysis on the Catalan and Spanish economies. Third, we can analyse the particular case of micro, small and medium-sized enterprises, which account for a very high proportion of the Spanish and Catalan productive fabric.

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in the medium-to-long term, the fact there is a learning curve for the company, or the fact that these effects appear after only minimal investment (Billión, Lera and Ortiz, 2007).

[3] Hellerstein, Neumark and Troske (1999) first used a database combining company and employee information in the American manufacturing sector to analyse the impact of the level of the level of education on business productivity. Meanwhile Doms, Dunne and Troske (1997) also used a database combining company and employee information to analyse the impact of the change in the workforce structure (producers versus non-producers) on business productivity.

It is also significant that, unlike in existing studies, we did not focus only on analysing the impact of human capital on business productivity, but we also considered the possibility of complementarity effects between the human capital and technologies used in the production process (AMTs) and how those effects can lead to higher productivity gains when combined properly[4]. Additionally, following the theory of skill-biased technological change, we analysed the effect of complementarity between new technologies and existing human capital in the various occupational groups with the aim of analysing whether investment in new technologies produces bias exclusively in the required skills for managers, or whether the bias extends to the skills required of production staff.

To do this we estimated the increase in the augmented Cobb-Douglas production function. Aware of the econometric problems arising when estimating production functions, we used the ordinary least squares (OLS) alternative estimation method proposed by Levinshon and Petrin (2003) to address the problems of unobservable heterogeneity and therefore endogeneity.

The results confirm the positive effect of human capital on business productivity, although this effect occurs indirectly through the use of AMTs, thus confirming the complementary relationship between the two. The results by occupational group confirm the importance of skilled staff in both management and production to maximise the productivity of new technologies, with managers and professionals as well as skilled operators playing a vital role. In sum, investment in human capital or new technologies alone is not sufficient; to ensure a significant improvement in business productivity we must combine both forms of investment.

We shall now explain how the different sections of this paper are distributed. The first section contains the theoretical discussion and empirical evidence of the effects of human capital on business productivity. The second section describes the database and the variables used in the analysis. The third and fourth sections present the methodology and results respectively. And the final section sets out the main conclusions from the work.

2. Theoretical framework and empirical evidence

[4] In the literature we can find some studies that analyse the effects of complementarity between human capital and technology, but these focus on the particular case of information and communication technologies (ICTs), such as investment in computers or Internet and intranet use. We looked instead at the specific case of advanced manufacturing technologies (AMTs).

The economics literature refers to three different effects of human capital. Firstly, it refers to human capital as an input factor in research and development (R&D) activities. This is the "research effect", on which there has been particular emphasis since the emergence of the endogenous growth theory (Romer, 1990 and Van Cayseele, 1990). The second, the "diffusion effect", refers to human capital as a factor in the diffusion of new technologies, and although there is no consolidated theory, the contributions of Nelson and Phelps (1966) and Bartel and Lichtenberg (1987) are significant. Third is the importance of human capital as a production factor, with the human capital theory (Becker, 1975) having focused on analysing the consequences of investment in human capital on the productivity of workers. This is known as the "work effect" or "assignment effect" (Cörvers, 1999).

The purpose of this paper is to analyse the relationship between the level of human capital and business productivity. We will therefore now focus on describing the theories that have analysed this relationship (the third effect).

As mentioned above, the impact of human capital as a production factor on work productivity has been studied according to the **human capital theory**, although other theories have also analysed its impact, such as the "**screening theory**" and the "**assignment theory**".

Human capital theory is based on the premise that workers invest in education to increase their level of human capital and this in turn increases productivity. According to this theory, education improves the labour productivity of individuals, resulting in higher wage increases. In order to improve their production efficiency, businesses should therefore invest in education either by training their existing staff or by hiring more-skilled staff (Becker, 1975; Psacharapoulos 1987; Blaug, 1976 and 1985).

Human capital theory thus argues that there is a causal relationship between education and productivity. But the assignment theory challenges that relationship[5]. The latter is founded upon the idea that individuals have certain skills that make them more productive than others, irrespective of their level of education. The cost of investing in the education of more skilled people is lower, since they need less time to acquire educational credentials. For this reason, individuals with higher productive skills (on average) invest more in education (Becker, 1975 and Hartog, 1993). If we accept this assumption that skills are related to academic success and

[5] Although there are several versions, we retain the ideas proposed by Arrow (1973) and Spencer (1973).

productivity in the workplace, this means that educational credentials indicate the most productive workers. Companies in search of indicators that can be correlated with productivity thus use these credentials to classify the most skilled people[6]. According to the screening theory, people's skills are not increased by initial education, but rather most of the necessary skills to be productive are learnt in the workplace, meaning education does not increase productivity.

The main difference between the two theories is on the issue of whether education increases people's productive ability during their school years. The human capital theory claims it does; the screening theory claims it does not. The existing empirical evidence rejects the strictest premises of the screening theory: that education does not increase productivity. A new version of the theory, referred to as the "weak" screening theory, subsequently appeared. This watered-down version no longer denies that there is a relationship between education and productivity through the provision of knowledge and skills. Indeed, according to Cövers (1999) "the 'weak' signalling theory can be considered complementary to the human capital theory in that educational qualifications also indicate the abilities, aptitudes and attitudes of individuals and that those are partly shaped and developed by the educational system". Thus, according to these theories human capital, measured by education, positively affects business productivity.

One thing to note when analysing the effect of human capital on business productivity is that workers develop their productive activity in a specific environment. This means the characteristics of the workplace could help individual workers to fully utilise their abilities and skills, which could affect their productivity. Thus, unlike the two previous theories, the assignment theory (or job-matching theory) proposes that the productivity of workers is determined both by their educational qualifications and by their workplace characteristics (Tinbersgen, 1956; Jovanovic, 1979; Sattinger, 1993). Workers with a certain level of education will therefore be more productive in certain workplaces than in others. This idea emphasises the importance of the optimal allocation of workers for business productivity (Hartog, 1988, 1992).

It is in this context that the skill-biased technological change (SBTC) theory makes sense. The main idea of SBTC is that there is a complementary relationship[7] between technology and human

[6] Similarly, in Thurrow's labour queue model (1975), companies use skills for signalling. This means workers at the top of the queue are hired first by the companies, because they have greater trainability and therefore cost less to train.
[7] As for the hypothesis of complementarity between capital and skills, Griliches (1969) and Fallon and Layard (1975) proposed a relationship of dependence between the marginal productivity of human capital

capital as a result of the improved learning capacity of skilled workers that maximises the potential of technology (Arrow, 1962)[8]. This means the introduction and diffusion of new technologies produces a relative increase in demand for skilled workers, which in turn results in an increase in the relative salaries of the most educated workers[9]. So, as these theories suggest, the introduction of new technologies in the workplace changes the skills required to achieve production efficiency. We can therefore expect the effect of human capital on productivity to be even greater in technologically advanced work environments.

In conclusion, the positive correlation between education and productivity can be explained by three alternative theories: the human capital theory, the screening theory ("weak" version) and the assignment theory. An important point to note is that some theories complement others, since each theory is based on different arguments that are not mutually exclusive. The more educated workers not only gain a higher level of human capital, which increases their productivity, but they also obtain certificates that can be used to improve the distribution of workers according to the skills they have acquired and those that are required in the different workplaces (Cövers, 1999)

Empirical evidence

Traditionally, the lack of data has meant that the methodology used to analyse the effects of human capital on productivity has been based on the estimated wage equation of workers. The human capital theory thus considers wages to represent the marginal productivity of individual workers, meaning that a positive impact of education on wages automatically leads to greater productivity. However, as Hellersten et al. (1999)[10] have already pointed out, using the estimated wage equation to determine whether education influences productivity has two serious drawbacks. Firstly, it requires the assumption of perfect competition; only if there is perfect

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and the capital stock. But it was not until the development of new technologies and the emergence of the "theory of skill-biased technological change" that this relationship of complementarity between human capital and capital – specifically technological capital – began to gain strength.

[8] Arrow's theories (1962) focus on the concept of "learning-by-doing" and how skilled workers are able to get the most out of the technology acquired by a company. A second view of the SBTC theory, which includes the ideas of Nelson-Phelps and focuses on explaining the complementary relationship between technology and human capital based on the premise that human capital facilitates the diffusion of technology, which means the positive correlation between the two factors is because companies with higher levels of human capital will incorporate new technologies faster.

[9] See Chennells and van Reenen (2002) for a summary of the literature.

[10] Hellersten et al. (1999) first analysed the direct impact of human capital on business productivity using a production function.

competition do wages reflect the marginal productivity of work. Secondly, wage differentials between workers may be due to differences in productivity or other factors, or to company characteristics such as different pay policies. This means wages would reflect not only worker productivity but also the characteristics of the different human resource policies used by the company.

Recently, new approaches have been developed that use the production function of the company to determine the impact of the human capital on business productivity[11]. These methods include the contributions of Hellerstein, Neumark and Troske (1999), Hellerstein and Neumark, (2004), Haskel, Hawkes and Pereira (2005) and Higon and Siena (2006). Although previous works seem to reach the conclusion that human capital does indeed have a positive impact on business productivity, there is a serious problem of bias, since none of the works takes into account the possible effects of technological capital on business productivity, nor the possible complementarity between the two production factors[12].

As mentioned above, this idea of complementarity between technology and human capital has been analysed using the SBTC theory. This theory is based on the fact that new technologies increase the demand for skilled workers, since they are able to use those technologies most efficiently, thus maximising business performance. The existing empirical evidence has shown a positive relationship between the use of new technologies and demand for skilled workers, as well as with wage increases[13]. But can workers with greater levels of human capital really increase the productivity of new technologies? Can a company improve productivity by having greater levels of technology and human capital?

We must therefore take into account that this positive relationship between new technologies and the demand for workers with a higher level of human capital can also be due to other factors such as the research effect or the diffusion effect of human capital. Companies operating in highly technological environments are demanding better educated workers because they promote both the diffusion and generation of new technologies (they have a positive effect on innovative

[11] Most studies use the Cobb-Douglas functional form. This simple form enables elasticities to be calculated without the introduction of too many terms that can make estimates imprecise (loss of degrees of freedom).

[12] The positive correlation between human capital and technologies can cause a bias in the estimated coefficient of human capital if technologies are not taken into consideration in the estimation. The coefficient of human capital could be reflecting the positive effects of technology on business productivity.

[13] For a review of the literature see Acemoglu (2002), Katz and Autor (1999), Link and Siegel (2003) and Dunne and Troske (2005).

capacity) without affecting the level of business productivity. Analysis of the correlation between new technologies and the level of education is therefore not sufficient to determine that workers who are more highly skilled raise the productivity levels of new technologies.

Significant works in this area of analysis include that of Bresnahan et al. (2002), which uses data from manufacturing and services companies throughout the EU, and those of Hempell (2003) and Arvanitis (2005), which focus on the services sector in Germany and Switzerland respectively. Those three works lead to the conclusion that technology and human capital are complementary factors. Both Bresnahan et al. and Hempell observe that educational qualifications do not directly affect business productivity, but rather that the positive correlation is as a result of the use of new technologies, although this relationship exists only for highly educated workers[14]. For example, Hempell observes that complementarity only exists for workers with university qualifications, and that no increase in the productivity of new technologies is found among workers with vocational qualifications.

The reason why these works have only found evidence of complementarity for workers with higher educational qualifications may be because the measures of technology used are based on information and communication technologies (computers, software, hardware, etc.)[15]. As highlighted by Aral et al. (2007), information and communication technologies (ICTs) can be particularly important for "information workers" such as managers, consultants, researchers, sales representatives, lawyers and accountants, and although it is true that technological change has changed the demand for skilled workers and the occupational structure of companies[16], this does not mean production workers should be underskilled[17]. The introduction of new technologies in production processes, such as the use of robotics, computer-assisted engineering programs, flexible-production systems, etc., may have resulted in production workers being substituted by machinery (Doms et al., 1997), but at the same time it may have increased the skills required for the technology to be used efficiently. This would be the case if it was demonstrated that not only is there a complementary relationship between new technologies and skilled workers in the area

[14] Arvanitis (2005) does not differentiate between different levels of education, but considers the human capital ratio of workers as a proxy with higher education.
[15] Bresnahan et al. (2002) use the logarithm of the value of computer equipment, Hempell (2003) takes the logarithm of ICT capital, and Arvanitis (2005) uses the percentage of workers who use the Internet and intranet as a proxy of ICT capital.
[16] Doms et al. (1997) underline that the introduction of new technologies has increased the demand for workers in the area of management (non-productive) at the expense of the demand for production workers.
[17] See Mañé (2001)

of management, but also the introduction of new production processes incorporating more advanced technology requires skilled workers in the area of production.

Because we have information on the AMTs, we are able to test this premise, which means our study goes beyond simply analysing the effects of human capital on business productivity. Our objective is to analyse whether these effects depend on the company's level of technology, and in particular the impact of new processing technologies on the productivity of workers in the area of production.

3. Statistical information and constructing variables

With the aim of analysing the effects of human capital on business productivity, we used microeconomic data from Catalan manufacturing firms taken from the 2001 Pimec-Sefes business server. The survey was conducted by telephone and included 757 companies and more than five employees.[18] The respondents, managers and heads of human resource departments were asked a series of questions on the characteristics of workers and production processes, as well as on the general characteristics of the company. The economic data used to measure business productivity were extracted from the Iberian Balance Sheet Analysis System (SABI)[19]. Due to the interaction of the two databases, the final sample was reduced to 615 companies. The main reason for this reduction was the absence of available data for some companies.

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Constructing variables

In our analysis, company output was measured in terms of gross value added at factor cost, physical capital based on the value of the tangible fixed assets, and the labour factor according to the number of workers on the payroll in 2001.

Regarding the construction of the human capital variable, we observed that there is no clear consensus on how it should be measured, but we do know that this concept includes aspects related to workers' production skills and abilities. Consistent with the human capital theory, the

[18] See the distribution of companies by size in Table 1 in the Annex.
[19] The SABI database is compiled using data from company accounts and reports in the Companies Register.

most common proxies have been the level of education, training and experience. In some studies, wages were also used as a proxy for production skills based on the assumption that workers' earnings reflect their marginal productivity. The main drawback of this approach is that earnings largely depend on remuneration policies and on the bargaining power of workers within the company[20].

In our study, we built our human capital measure using data from questions 8 and 9 of the 2001 Pimec-Sefes business survey.

Comentario [0901752]: A la taula, la part ressaltada ficava (LLEGIR, MÚLTIPLE) al text original. No ens queda clar què vol dir, així que hem fet la traducció (READ, MULTIPLE) però ens agradaria que ens conformessis que sigui correcta.

8. **Please state how many of the following occupations exist in your company. (READ, MULTIPLE).** *(DK/NA 999)*

(no.)

a) Managers .... __________ If 0 or DK/NA, do not answer p.9.a or p.10.a
b) Professionals or technicians .... __________ If 0 or DK/NA, do not answer p.9.b or p.10.b
c) Administrative or sales staff .... __________ If 0 or DK/NA, do not answer p.9.c or p.10.c
d) Skilled workers (workshop managers, tradespersons) .... __________ If 0 or DK/NA, do not answer p.9.d or p.10.d
e) Unskilled labourers .... __________ If 0 or DK/NA, do not answer p.9.f or p.10.e
f) Operators (production-line workers) .... __________ If 0 or DK/NA, do not answer p.9.e or p.10.f
g) Public-contact workers) .... __________ If 0 or DK/NA, do not answer p.9.e or p.10.g

9. **Level of training (arrival, MULTIPLE)** (Ns / Nc 999) ....

(no.)

a) How many of the current managers hold a bachelor's degree or higher? .... __________
b) How many of the current professionals or technical staff hold a bachelor's degree or higher? .... __________
c) How many of the current administrative or sales staff hold an FP2 or COU diploma or higher? .... __________
d) How many of the current skilled workers hold an FP2 or COU diploma or higher? .... __________
e) How many of the current unskilled labourers hold at least an FP1 or BUP diploma? .... __________
f) How many of the current operators hold at least an FP1 or BUP diploma? .... __________
g) How many of the current skilled public-contact workers hold secondary school qualifications or higher? .... __________

Thus our measure of human capital has been built using the level of education of workers by occupational group. Unlike other studies, this measure puts special emphasis on the assignment theory and on the importance that the characteristics of the workplace has on the worker's skills, and therefore on the minimum required level of education to perform tasks efficiently. Thus, our measure is not so much the level of education of the company's workers, but also the proportion of skilled workers.

In the classification between skilled and unskilled workers, both managers and professional and technical staff will have the necessary skills to carry out the tasks required in their workplace, and

[20] To solve these problems, new approaches have emerged that propose the estimation of personal fixed effects using wage equations and by checking company-specific effects (Abowd, Kramarz and Margolis, 1999).

they shall therefore be considered skilled if they hold at least a university degree or diploma. Administrative and sales staff (floor managers and tradespersons) are considered skilled if they possess a minimum level of education of FP2 or COU. Finally, operators and labourers are required to have skills equivalent to those obtained in FP1 or BUP to be considered skilled in their workplace[21].

Following these criteria, we constructed an aggregate human capital index that was measured as the percentage of skilled workers in the total workforce. We also created various human capital indices according to occupational group, such as the percentage of managers who are skilled[22].

Constructing these human capital indices for each occupational group enabled us to analyse the complementarity between the production technologies and the human capital of the different categories of workers. It also enables us to test the premise that technological change increases demand for skilled production workers.

We constructed the measure of technology based on the work of Doms et al. (1997). The measure is based on the type of production machinery used in the plant (AMTs). Thus, unlike other works that focus on analysing the impact of ICTs – such as office machinery, computers, communication equipment, etc. – we used nine different production technologies, which can be complementary to each other and, by their nature, can be used in any manufacturing industry. These advanced manufacturing technologies include numerically controlled machine tools, robotically assisted production, CAD-controlled machines, computer-assisted engineering (CAE) programs, automated warehouse management systems, flexible production systems, laser technology for work on materials, intranet data sharing and automatic sensors for inputs and output control. Our technological measure is based on the assumption that companies that use a greater number of technologies are more technologically advanced[23]. This enabled us to produce a classification of companies with three levels of technological complexity: fewer than two technologies = low-technology; between two and three technologies = medium-technology; more than four technologies: high-technology.

[21] The Annex contains the equivalences according to the International Standard Classification of Occupation (ISCO-08) and the International Standard Classification of Education (ISCED-97).
[22] In the estimation we monitored the structure of the workforce (the percentage of total workers in each occupational group).
[23] Although this way of measuring the company's level of technology does not take into account the intensity of use of this technology, Doms et al. (1997) show that the number of technologies is a good proxy for intensity of use.

Among the control variables we used in the regression we must distinguish between variables that refer to business-specific effects and those that refer to industry-specific or region-specific effects.

The first group includes a dummy variable that attempts to capture the effects of the experience of workers on business productivity. The value of this variable is 1 if the number of workers with more than two years' experience is above average and 0 if it is not. We also introduced the variable "company age" as a proxy for experience, and the variable "age squared" in order to capture any reduction in performance resulting from this variable. Regarding the effect of international competition on business productivity, the available evidence suggests that the greater the foreign competition, the greater the business productivity. This is not surprising, it is essential to ensure production efficiency to survive in highly competitive environments[24]. We thus introduced a dummy variable into the regression that takes the value 1 if the company competes in foreign markets and 0 otherwise. We also introduced the variable of the proportion of exports out of the company's total sales. Unlike the previous variable, which only indicates whether the company exports or not, this variable measures the extent to which the company operates in foreign markets.

In order to capture the industry-specific effects we have introduced sectoral dummy variables[25]. These dummies allow us in particular to determine sector-specific variations in companies' outputs that cannot be explained by production factors, such as fluctuations in demand produced by the specific economic cycle of the industry. They also ensure that companies' production can be compared across industries, detecting measurement errors resulting from industry prices, which is one of the main problems that Griliches and Klette (1996) identify in the analysis of productivity at the business level.

With the same aim of monitoring regional productivity stocks, we introduced dummy variables for the different regions: the Barcelona Metropolitan Area, the rest of the province of Barcelona, Terres de l'Ebre, the rest of the Tarragona province, and the provinces of Lleida and Girona.

3. Econometric model

[24] Serrano, Requena, Lopez-Bazo and García-Sanchis (2005) analyse the impact of foreign trade and human capital on the total productivity of the factors of Spanish industry.

[25] Two-digit CNAE code

The impact of human capital on business productivity was analysed using the Cobb-Douglas specification to approximate the production function. The advantage of using this type of function is that we can break down the different production factors, which allows us to easily calculate the contribution made by each factor to the company's productivity and does not require the restriction of constant returns to scale to be imposed.

The modelling of the human capital factor in the production function can be done in two different ways based on the works of Griliches (1970) and Fallon (1987). The first way is through the use of the measure of actual work or job quality[26], and the second is through the introduction of human capital as an additional factor in the traditional production function. In this work we have chosen the second approach, based on the works of Bresnahan et al. (2002), Arvanitis (2005) and Hempell (2003), since it enables us to derive the various indices in the production function[27]. The analytic expression of the function will take the following form:

$$lnY_t = lnA_t + \beta_K lnK_t + \beta_L lnL_t + \beta_{KH} KH_t + \beta_T TECH_t$$

$$lnY_t = lnA_t + \beta_K lnK_t + \beta_L lnL_t + \beta_{KH} KH_t + \beta_T TECH_t \beta\beta lnA_t = \beta_0 + \omega_t + \eta_t \beta_0 \beta_0 \eta\eta\omega\omega$$

$$lnY_t = \beta_0 + \beta_K lnK_t + \beta_L lnL_t + \beta_{KH} KH_t + \beta_T TECH_t + \omega_t + \eta_t$$

$$F(1,1) - F(0,1) \geq F(1,0) - F(0,0) F(1,1) \geq F(0,1) + F(1,0) F(1,1) \geq F(0,1) + F(1,0)$$

$$\beta_{11} \geq \beta_{01} + \beta_{10} \; H_0 : \beta_{11} - \beta_{01} - \beta_{10} \geq 0 \quad vs \quad H_1 : \beta_{11} - \beta_{01} - \beta_{10} < 0$$

$$Contraste1; \; H_0 : \beta_{11} - \beta_{01} - \beta_{10} = 0 \quad vs \quad H_1 : \beta_{11} - \beta_{01} - \beta_{10} \neq 0$$

$$y$$

$$Contraste2; \; H_0 : \beta_{11} - \beta_{01} - \beta_{10} = 0 \quad vs \quad H_1 : \beta_{11} - \beta_{01} - \beta_{10} < 0$$

$$F(1,1) - F(0,1) \geq F(1,0) - F(0,0) lnY_t = lnA_t + \beta_K lnK_t + \beta_L lnL_t + \beta_{KH} KH_t + \beta_T TECH_t$$

Where *Y* is the company's output, *K* and *L* are the traditional production factors "capital" and "labour", and *KH* and *TECH* are additional functions we have added that represent the "human capital" factor and the level of technology of the company respectively, that is, the quality of the factors "labour" and "capital". The parameters are as follows: β represents the output elasticities for each of the production factors, while *A* represents the total productivity of the factors, which is calculated as follows:

[26] See Hellerstein et al. (1999) and Haskel et al. (2003, 2005) for an effective application of effective work or quality of work in the production function.

[27] However, Griliches (1970) shows that it is impossible to differentiate empirically between the two forms of prior specification.

$$lnA_t = \beta_0 + \omega_t + \eta_t$$

Where: β_0 represents the common technical progress for all companies in manufacturing, η represents the random disturbance term and ω represents the company's unobserved productivity.

By joining together the two expressions above and reordering them we obtain the Cobb-Douglas production function.

$$lnY_t = \beta_0 + \beta_K lnK_t + \beta_L lnL_t + \beta_{KH} KH_t + \beta_T TECH_t + \omega_t + \eta_t$$

Based on the work of Olley-Pakes (1996), ω cannot be observed from an econometric perspective, but it can from a company perspective. This implies that decisions to invest in both human capital and technologies will depend on this unobserved productivity, thus creating an endogeneity problem, and therefore a bias in the estimation of the parameters of the regression. We solve this problem by using the methodology proposed by Levinshon and Petrin (2003), which allows the value of ω to be approximated using a semi-parametric estimation technique. [28]

4. Results

Table 2 of the Annex shows the descriptive statistics of the variables, taking into consideration the entire sample and classifying the companies according to apparent labour productivity (value added per worker). We can see that the variables "human capital interest" and "level of technology" increase in value as the average productivity increases[29]. We can also see that the companies in the sample generally have a low level of technology, as only 18.8% of them have implemented four or more technological elements into their production processes. Regarding the level of human capital, we can observe that on average 44% of workers in Catalan companies

[28] The greatest criticism of the methodology proposed by Olley-Pakes (1996) is that it uses the investment by the company as a proxy for unobserved productivity. This implies that investment must be positive for the condition of invertibility to be fulfilled and thus for the function to be estimated. As Levinsohn and Petrin point out (2003), many companies do not invest, so these should be removed from the sample, which causes a truncation problem. To avoid this problem, Levinsohn and Petrin propose using the variable "material" as a proxy variable for unobserved productivity. This paper has chosen to use "materials" as a proxy variable for productivity due to the large proportion of companies that did not invest during the period we analysed.

[29] The difference of means test rejects the null hypothesis of equal means between groups and confirms that the more productive companies are those with higher average levels of both human capital and technologies.

appear to be skilled to do their job efficiently. We can also see that the greatest gap between the level of education needed in a workplace and the level actually attained is found among production workers. Finally, we should mention that the data show that the most productive companies tend to be larger (in terms of number of staff), older (age) and bigger exporters.

Table 3 of the Annex shows the results of the estimation of the production function without taking into account the effects of complementarity between human capital and production technologies[30]. The first three models were estimated using ordinary least squares (OLS), while the others were estimated using the methodology proposed by Levinshon and Petrin (2003), which enables us to solve the problems of endogeneity caused by companies' unobserved productivity. This means that, as we might expect, the results obtained using the OLS method create an upward bias for both the "labour" factor and the "human capital" factor[31]. The main reason for this bias is the nature of the "labour" factor work and the ease of adjustment to productivity changes or shocks compared with other factors such as the level of technology.[32] Since the OLS method produces a bias in the estimation of the parameters, we will focus on the discussion of the results obtained using the linear programming (LP) method. Model 4 includes the "human capital" variable but not the "technology" variable; Model 5 includes the "human capital" variable but not the "technology" variable; and model 6 includes the different human capital indices by occupational group as well as the "technology" variable.

The coefficient of the dummy variable for workers' experience should be interpreted with caution. Remember that this dummy variable takes the value 1 if the percentage of workers with more than two years' experience is higher than the industry average. We would therefore expect that the companies experiencing the most growth would be those with a lower percentage of workers falling into that category, so the value of this dummy variable could be 0 for companies in expansion. This means that the dummy variable may be detecting productivity differences between companies that are growing and those that are not, so the negative sign of the variable should not surprise us, even though it is not very significant (Model 4) or insignificant (Model 5).

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[30] In all estimates, workforce distribution was introduced as a control variable along with the sector-specific and region-specific dummy variables.

[31] To identify the human capital coefficient we should complete the second stage of the LP procedure, but this would require having the variables delayed for at least 1 period. The cross-sectional data only allow us to complete the first step of the LP procedure, making it impossible to calculate the human capital coefficient (see Arnold et al., 2005).

[32] See Ackerverg, Caves and Frazer (2005) and Van Biesebroeck (2007) for an empirical study of the effect of unobserved productivity on the value of the coefficients in the production function.

If we look at the variables referring to the companies' experience (age and age squared), we see that the accumulation of experience by a company has a significant positive effect on its business productivity, although that effect decreases over time. An inverted-U relationship is thus confirmed between the age and productivity of the company, as is postulated by the industrial development models of young companies. These models assume that new companies have lower productivity levels but that they gradually learn as they make new investments, operate in international markets or increase their scale of production. There is a learning-by-doing process, which increases business productivity through the accumulation of experience, especially during the company's first years, but then the accumulation of knowledge through learning-by-doing loses weight in the explanation of productivity improvements (Fernandez, 2006).

Regarding the impact of exports on business productivity, in the literature on international trade we find two hypotheses to explain higher levels of productivity in countries that export. The first refers to the premise of selection and the fact that the existence of sunk costs (e.g. the internal organisation) associated with entry into foreign markets means that only the most productive, most competitive companies can enter. The second hypothesis is based on *learning-by-exporting*, and assumes that companies involved in international markets can benefit from international contacts and spillovers of technological knowledge. The main difference between the selection hypothesis and the learning-by-exporting hypothesis is that the former does not consider there to be a causal relationship between exports and business productivity. In our study, we found very different results depending on the estimation method used. The estimation by OLS suggests that participating in international markets has a positive effect on business productivity[33]; however, when we measure companies' unobserved productivity using the LP methodology, we observe a decrease in the value and significance of the "export" variable. These results support the selection hypothesis, so the significant positive value of the coefficient obtained using OLS could be detecting the positive effect of better organisation and higher levels of unobserved productivity in companies that export. That is why once unobservable productivity has been brought under control, the effects of whether a company competes in international markets disappears[34]. Indeed, not only does the coefficient of this variable become insignificant, but also the companies that export the most are the least productive. One possible explanation for these results could be

[33] These results are coherent with those obtained by Kraay (1999), Blalock and Gertler (2004) and Fernandes and Isgut (2006).
[34] Sen et al. (2002) analyse the effect of exports on productivity in Spanish manufacturing firms and obtain evidence to support the selection hypothesis. However, the evidence in favour of learning-by-exporting is very weak and is limited to younger firms. Arnold and Hussinger (2005) find the same results for German manufacturing companies.

linked to the country's specialist export product, since traditionally companies with the largest export capacity belonged to low-technology sectors, and therefore less productive sectors. This would imply that although these companies might be the most productive in their sector, they cannot compete with the productivity levels achieved by companies in sectors with more advanced technology that also compete in international markets but with a lower volume of exports[35].

As mentioned above, the difference between models 4 and 5 is that in Model 4 technology variables have not been introduced into the regression. This means that the aggregate human capital (KH), approximated as the percentage of skilled workers out of the total workforce, makes a significant positive contribution to business productivity. However, the introduction of the level of technology into the estimation makes the human capital coefficient insignificant [36](Model 5). This is explained by the positive correlation between the two factors, causing an overestimation of the coefficient if one of them is omitted from the equation[37]. Thus, according to Model 5, aggregate human capital would have not have any effect, at least not directly, on the productivity level of Catalan companies.

The problem of considering the aggregate measure of human capital is that we cannot analyse the contribution of different types of workers on business productivity. In order to solve this problem, in model 6 we have introduced different human capital indices by occupational group, allowing us to test whether there exists any kind of key worker that directly influences productivity. The results showed that one crucial element affecting productivity is the percentage of skilled

[35] Therefore of the 271 companies in the sample that compete in international markets, 55.2% are low-technology and 44.7% are high-technology. Regarding the percentage distribution of sales, we see that companies in the highest quintiles of distribution belong to the low-technology sectors, which shows that companies with greater penetration into foreign markets are companies in sectors in which there is a low technological intensity, such as food and beverages, wood and rubber, and textiles.
[36] These results are in line with those given in existing literature. Hellerstein et al. (1999), Hellerstein and Neumark, (2004), Haskel et al. (2005) and Higón and Siena (2006) find that human capital has a positive effect on business productivity, but they do not include the effect of technologies in their analysis. Instead Bresnahan et al. (2002) and Hempell (2003), who do include the technology variable in the production function, do not observe a direct effect of human capital on business productivity.
[37] These results seem to corroborate the premises of the SBTC theory and to highlight the importance of analysing human capital and technology as two complementary factors in the production function

professionals: a 1% increase in this type of worker would lead to a 9.7% increase in productivity irrespective of the company's level of technology[38].

The impact of AMTs on business productivity appears to be positive and significant, as companies with high or medium level of technologies have productivity levels that are respectively 17.3% and 7% higher than those obtained by low-technology companies (Model 5).

5. Analysis of complementary human capital and technology.

We analysed the effect of complementarity between human capital and the level of technology on the production function using the formulation postulated by the theory of supermodularity (Topkis, 1998 and Athey and Stern, 1998). The theory assumes that if there are two types of activities (A_1 and A_2), each activity can be transformed into $(A_i = 1)$ if the company carries it out and $(A_i = 0)$ if it does not. Thus the function $F(A_1, A_2)$ is "supermodular" only if it satisfies the following condition:

$$F(1,1) - F(0,1) \geq F(1,0) - F(0,0)$$

If this condition exists we can say that A_1 and A_2 are complementary activities. If a company decides to conduct a certain activity, the effects on the function F will be greater if the company also conducts the second activity. In our study, the function F represents the company's productivity, the activity A_1 defines whether the company's human capacity is above average (A_1=1) or below average (A_1=0), and the activity A_2 defines whether the company has a high technological capacity (A_2=1 for four or more technologies, and A_2=0 for fewer than four). If the premise of complementarity is true, then the effects of having skilled human capital on business productivity would be greater in companies with more advanced technology.

In our estimation we standardised $F(0,0)=0$, so the conditioned complementarity becomes:

$$F(1,1) \geq F(0,1) + F(1,0)$$

An alternative to the theory of supermodularity to analyse the complementarity between human capital and technology is simply to introduce the aforementioned interacting variables in

[38] The introduction of different rates of one-to-one human capital does not alter the results of joint estimation.

accordance with the methods proposed by Bersnahan et al. (1999) or Hempell (2003). However, this method is not recommended if continuous variables are not available, since intermediate cases would not be identified (Leiponen, 2002 and Arvanitis, 2005).

Tables 4 and 5 show the results of estimating the production function considering the hypothesis of complementarity between the company's human capital and level of technology[39]. Comparing the results according to the OLS and LP methods shows that the main difference is in the value of the estimated coefficients and not in the significance. As we have already mentioned, the OLS method produces a bias in the estimation, so we focused on analysing the results obtained using the LP method (Table 5).

In order to test whether there is complementarity between human capital and technologies we introduced three dummy variables into the production function that represent the possible statuses of the companies. The S_{11} status takes the value 1 for high-technology (more than four technologies) companies with an above-average percentage of skilled workers, and 0 otherwise. The S_{10} status takes the value 1 for non-high-technology companies with an above-average percentage of skilled workers, and 0 otherwise. The S_{01} status takes the value 1 for high-technology companies with a below-average percentage of skilled workers, and 0 otherwise. And the S_{00} status (reference category) takes the value 1 for non-high-technology companies with a below-average percentage of skilled workers, and 0 otherwise.

The introduction of dummy variables into the regression will subsequently allow others to test the condition of complementarity:

$$F(1,1) \geq F(0,1) + F(1,0)$$

If we translate the previous expression in terms of the regression coefficients we find:

$$\beta_{11} \geq \beta_{01} + \beta_{10}$$

The hypotheses to be tested will therefore be:

$$H_0 : \beta_{11} - \beta_{01} - \beta_{10} \geq 0 \qquad vs \qquad H_1 : \beta_{11} - \beta_{01} - \beta_{10} < 0$$

To perform a one-tailed test in which the null hypothesis includes both equal and unequal values is the same as to test the following two contrasting hypotheses:

[39] The control variables "workforce distribution", "sector" and "region" were introduced into all estimates.

$$Contraste1;\ H_0: \beta_{11} - \beta_{01} - \beta_{10} = 0 \qquad vs \qquad H_1: \beta_{11} - \beta_{01} - \beta_{10} \neq 0$$
$$y$$
$$Contraste2;\ H_0: \beta_{11} - \beta_{01} - \beta_{10} = 0 \qquad vs \qquad H_1: \beta_{11} - \beta_{01} - \beta_{10} < 0$$

Non-rejection of the null hypothesis in Contrast 1 is sufficient to consider that the condition of complementarity has been met. Only if the null hypothesis in Contrast 1 is rejected is it necessary to use Contrast 2[40].

The results of the estimation (Table 5) firstly showed that the value of the "labour" factor coefficients and the control variables (workers' experience, company age and international competition) are not altered when the previous human capital and technology variables (Model 5 and 6 and Table 3) are replaced by the new status variables S_{11}, S_{10}, S_{01}. Second, the results of Model 1 show that a complimentary relationship does indeed exist between human capital and technology, since the value of the statistical test of Contrast 1 is 0.06, which means the null hypothesis of complementarity cannot be rejected. Moreover, the coefficient of the status S_{11} is positive and significant, indicating that high-technology companies with an above-average percentage of highly skilled workers are 15.4% more productive than companies with less-skilled workers and lower technology. At the same time, when these companies are compared with those with status S_{01}, that is, high-technology companies with a low human capital, the (S_{11}) companies' productivity is 4.2% higher.

In sum, the evidence indicates that human capital does indeed have a significant positive effect on business productivity, although this impact passes through the use of new technologies. Therefore, as predicted by the SBTC theory, to maximise the potential of new production technologies, a skilled workforce is required. Only the combination of these two factors can maximise a company's productivity.

The question we still must analyse is whether this complimentary relationship that is satisfied at the aggregate level is also fulfilled for different types of workers. To analyse whether the productivity of new technologies depends on workers' skills only in the area of management or whether the skills of production workers is also important, we tested the aforementioned complementarity hypothesis on each occupational group. Model 2, for instance, compares the hypothesis of complementarity between new production technologies and skilled managers. The

[40] See Delgado, Fariñas and Ruano (2002).

variable status S_{11} now acquires the value 1 for high-technology companies with an above-average percentage of skilled managers and 0 otherwise. The S_{10} status takes the value 1 for non-high-technology companies with an above-average percentage of skilled managers. Finally, the S_{01} status takes the value 1 for high-technology companies with a below-average percentage of skilled managers and 0 otherwise[41].

From the results we must first conclude that in all cases the test statistic leads us not to reject the null hypothesis, thus confirming the importance of having skilled workers in all occupational groups to maximise the productivity of advanced manufacturing technologies (AMTs). As highlighted by Arvanitis (2005) a more skilled workforce can on the one hand increase the benefits of using new technologies, and on the other hand, these new production systems that incorporate advanced technology generate a lot of information that requires highly skilled workers who can use it properly. The results thus cast doubt on the assumption that production workers are underskilled as a result of the introduction of new technologies.

Secondly, there are differences in the contribution of different occupational groups to business productivity. Thus, within the area of management and leadership, both managers and skilled professionals (Model 2 and 3) play a crucial role in explaining the impact of technology on productivity (the coefficient S_{01} is not significant in any cases). High-technology companies with skilled managers are on average 13.6% more productive. This figure increases to 25.8% among high-technology companies with skilled professionals. With regard to skilled professionals, the above conclusions remain as they form the only occupational group that positively and significantly affects the productivity of the company regardless of the level of technology (S_{10} positive and significant). Thus, low-technology companies with an above-average percentage of skilled professionals are 8.2% more productive than low-technology companies with an below-average percentage of skilled professionals.

In the remaining occupational groups, we see that the productivity of technologies depends exclusively on the skills of workers (S_{01}, for the other groups there is a significant positive correlation), but the combination of technologies and highly skilled workers does produce higher productivity levels (complementarity hypothesis). Among production workers, skilled operators are an important factor for the impact of new technologies on business productivity. High-

[41] As control variables, in addition to occupational structure, industry and region, the percentage of skilled workers in the other occupational groups was also introduced.

technology companies with a below-average percentage of skilled workers increase productivity by only 12.1%; however, high-technology companies with an above-average percentage of operators increase productivity by 16.5%.

Finally, we should mention the results obtained from administration and sales staff (Model 4) and skilled labourers (Model 7). Firstly, they are the only groups with a positive but insignificant coefficient for the S_{11} dummy variable, although the complementarity hypothesis cannot be rejected. This seems to indicate that although the productivity of new technologies does not seem to depend much on the skills of these workers, companies do obtain a greater performance from this type of human capital when they have higher levels of technology, so the S_{10} coefficient is lower in both cases than the S_{11} coefficient. The reason why the low impact of skills of administration and sales staff on the productivity of new production technologies is that these technologies are used in the production process, which means they have little influence on the daily tasks of these workers[42]. Perhaps the results would have been different if information and communication technology had been taken into consideration. The low impact of skilled labourers on the productivity of new technologies may be because these technologies automate production processes, completing the tasks of the labourers and thus replacing them with machinery. This means the productivity of these workers does not depend so much on the labourers but more on the operators responsible for supervising and monitoring the production processes to ensure they function correctly.

6. Conclusions

The aim of this study is to extend existing knowledge on the impact of human capital on business productivity based on the premise of complementarity between human capital and level of technology. The differences with other works are: First, the human capital index was constructed with special emphasis on the assignment theory and the importance of the skills needed by occupational group. Second, the level of technology of the company refers to technologies used in

[42] The effect of complementarity between skilled administrative and sales staff and sales representatives and new production technologies cannot be rejected, possibly because companies with advanced production processes have also invested in information and communication technologies, since the coefficient of technological complexity may in part be reflecting the effects of complementarity between ICTs and administrative staff and sales representatives.

the production process (CAD, CAE, automated warehouse management systems, etc.) and not to information and communication technologies (computers, software, hardware, etc.). Third, to test the existence of groups of key workers in business productivity, we analysed the hypothesis of complementarity between technology and human capital for each occupational group.

We performed the analysis taking into consideration data on Catalan manufacturing companies from the 2001 Pimec-Sefes business survey (2001). To do this we estimated the Cobb-Douglas production function using the semiparametric method proposed by Levinshon and Petrin (2003) to correct the problems of endogeneity caused by unobserved productivity.

The effect of complementarity between human capital and level of technology on business productivity was analysed following the formulation postulated by the theory of supermodularity, testing the hypothesis that the effects of human capital on productivity are greater for high-technology companies.

$$F(1,1) - F(0,1) \geq F(1,0) - F(0,0)$$

The results lead us not to reject the hypothesis of complementarity between human capital and technologies and confirm the premise of the theory of skill-biased technological change. Thus, high-technology companies with an above-average percentage of skilled workers are 15.4% more productive than companies with less skilled workers and lower levels of technology, and 4.4% more productive than high-technology companies with low human capital.

The results by occupational group confirm the importance of skilled staff in both occupational group to maximise the productivity of new technologies. In the area of management, both managers and skilled professionals play a crucial role in explaining the impact of technology on productivity. Among production workers, operators play an important role in the production efficiency of new process technologies. Therefore the combination of high levels of both factors increases business productivity by an average of 16.5%, an increase that is 4 percentage points higher than that achieved by high-technology companies.

In short, the evidence provided shows that having skilled workers in management is not enough to reach the highest level of productivity in technologically advanced environments. The skills of production workers, especially operators, is essential in order to achieve greater productivity through efficient use of new process technologies.

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Annex

Table 1: ISCO-08 Structure, Group Titles and Codes

Code	Description	Categories
1.	Managers	▪ Managers ISCO-08: 1
2.	Professionals	▪ Professionals and technicians ISCO-08: 2 and 3
3.	Technicians and associate professionals	
4.	Clerical support workers	▪ Clerical and sales workers ISCO-08:4 and 5
5.	Service and sales workers	▪ Skilled workers ISCO-08: 6 and 7
6.	Skilled agricultural, forestry and fishery workers	▪ Machine operators ISCO -08: 8
7.	Craft and related trades workers	▪ Labourers ISCO-08: 9
8.	Plant and machine operators, and assembles	▪
9.	Elementary occupations	
10.	Armed forces occupations	
11		

Table 2: ISCED-97

Code	Description	Equivalences
x.	No schooling	▪ ISCED-97 5
0.	Pre-primary education	▪ FP2/COU ISCED-97: 3 and 4
1.	Primary education or first stage of basic education	▪ FP1/BUP ISCED-97: 2
2.	Lower secondary or second stage of basic education	
3.	Upper secondary education	
4.	Post-secondary non-tertiary education	
5.	First stage of tertiary education	
6.	Second stage of tertiary education	
7.		

Table 3: Classification by qualifications

- Managers are skilled if their educational level is 6
- Professionals and technicians are skilled if their educational level is 6
- Clerical and sales workers are skilled if their educational level is 3 or 4
- Skilled workers are skilled if their educational level is 3 or 4
- Machine operators are skilled if their educational level is 2
- Labourers are skilled if their educational level is 2

Table 1- Distribution of companies by size

Size	Number of companies	% of the sample
Microenterprises	187	30.4
Small	380	61.8
Medium-sized	48	7.8
Total	615	100

Note: Microenterprises (5-9 workers), small enterprises (10-49 workers), medium-sized enterprises (50-250 workers).

Table 2- Characteristics of the sample

		Total		Low productivity		Medium productivity		High productivity	
	Variable	Medium	St. Dev.	Medium	St. Dev.	Medium	Est. Dev.	Medium	St. Dev.
Gross added value per worker	VABpo	31397	31634	14349	4561	26521	3666	53452	46754
Gross added value per worker	Kpo	20529	34637	11782	32562	15460	19444	34438	43402
Number of workers	L	23.55	44.72	18.96	22.65	19.83	20.99	31.93	70.59
% skilled workers	KH	0.440	0.282	0.394	0.285	0.425	0.267	0.503	0.284
% skilled managers	KHdir	0.433	0.452	0.372	0.453	0.395	0.452	0.532	0.436
% skilled professional and technical staff	KHprof	0.348	0.446	0.228	0.396	0.352	0.445	0.465	0.465
% skilled administrators and	KHadm	0.678	0.425	0.620	0.461	0.701	0.416	0.714	0.389

sales staff									
% skilled workshop managers and tradespersons	KHencarg.	0.384	0.417	0.365	0.417	0.361	0.408	0.426	0.425
% skilled operators	KHoper	0.156	0.316	0.142	0.307	0.156	0.334	0.170	0.306
% skilled labourers	KHpeon	0.215	0.353	0.200	0.348	0.211	0.344	0.235	0.369
Dummy: companies with above-average % of workers with more than 2 years' experience	Exper	0.583	0.493	0.609	0.489	0.601	0.490	0.539	0.499
total number of technologies	----	2.01	1.69	1.72	1.71	1.93	1.62	2.38	1.67
Dummy: low-technology companies	TECH bajo	0.443	0.497	0.526	0.500	0.466	0.500	0.338	0.474

Table 2 (ctd.)

Dummy: medium-technology companies	TECH medio	0.367	0.482	0.331	0.472	0.383	0.487	0.387	0.488
Dummy: high-technology companies	TECH alto	0.188	0.391	0.141	0.349	0.150	0.358	0.274	0.447
Dummy: exporting companies	Expor	0.440	0.496	0.312	0.464	0.470	0.500	0.539	0.499
% sales in international markets	%Expor	0.109	0.194	0.092	0.195	0.098	0.169	0.138	0.212
age	age	26.16	24.46	22.84	24.25	26.92	23.40	28.72	25.46
Total		615		205		206		204	

Note: Companies classified by productivity tertiles

Table 3 – Estimation of the augmented Cobb-Douglas production function

	Model 1 (OLS)		Model 2 (OLS)		Model 3 (OLS)		Model 4 (OLS)		Model 5 (OLS)		Model 6 (OLS)	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
logK	0.1650***	*0.0208*	0.1596***	*0.0211*	0.1537***	*0.0215*						
logL	0.8286***	*0.0416*	0.8083***	*0.0439*	0.7913***	*0.0455*	0.5635***	*0.0449*	0.5417***	*0.0463*	0.5348***	*0.0473*
KH	0.2255***	*0.0838*	0.1983**	*0.0849*			0.1327*	*0.0693*	0.1008	*0.0707*		
KH(dire)					0.0056	*0.0564*					-0.0350	*0.0458*
KH(prof)					0.1602***	*0.0519*					0.0973**	*0.0418*
KH(adm)					-0.0006	*0.0523*					-0.0144	*0.0435*
KH(encarg)					0.0318	*0.0567*					-0.0035	*0.0459*
KH(oper)					0.0386	*0.0729*					0.0196	*0.0624*
KH(peon)					-0.0392	*0.0608*					0.0017	*0.0522*
Exper	-0.0869**	*0.0432*	-0.0807*	*0.0433*	-0.0812*	*0.0440*	-0.0652*	*0.0359*	-0.0557	*0.0354*	-0.0533	*0.0358*
TECH												
medium			0.0269	*0.0484*	0.0199	*0.0488*			0.0684*	*0.0411*	0.0701*	*0.0418*
high			0.1555**	*0.0721*	0.1679**	*0.0724*			0.1566***	*0.0566*	0.1734***	*0.0574*
%Expor	-0.0982	*0.1645*	-0.0945	*0.1659*	-0.1036	*0.1721*	-0.2324*	*0.1300*	-0.2299*	*0.1294*	-0.2241*	*0.1329*
Expor	0.1367**	*0.0573*	0.1319**	*0.0573*	0.1367**	*0.0579*	0.0387	*0.0478*	0.0329	*0.0476*	0.0364	*0.0486*
age	0.0057***	*0.0016*	0.0055***	*0.0016*	0.0052***	*0.0016*	0.0037***	*0.0013*	0.0033**	*0.0013*	0.0032**	*0.0013*
age*age	-3.14E-05***	*1.10E-05*	-3.11E-05***	*9.88E-06*	-3.06E-05***	*9.52E-06*	-2.21E-05***	*7.39E-06*	-2.13E-05***	*7.17E-06*	-2.09E-05***	*7.25E-06*
N	615		615		615		615		615		615	
R^2	0.7694		0.7716		0.7735		0.8447		0.8469		0.8476	

NB: the dependent variable is the gross added value algorithm. Heteroskedasticity-robust standard errors (White procedure). Control variables: occupational structure, sectoral and regional dummies. ***, ** and * denote statistical significance of 1%, 5% and 10% respectively.

Table 4 – Estimation of the augmented Cobb-Douglas production function taking into consideration the complementarity effect (OLS).

	Model 1 (KH)		Model 2 (KHdire)[a]		Model 3 (KHprof)[a]		Model 4 (KHadm)[a]		Model 5 (KHenca)[a]		Model 6 (KHoper)[a]		Model 7 (KHpeon)[a]	
	Coef.	St. Dev.	Coef.	St. Dev.	Coef.	St. Dev.	Coef.	St. Dev.	Coef.	St. Dev.	Coef.	St. Dev.	Coef.	St. Dev.
logK	0.1599***	*0.0211*	0.1542***	*0.0216*	0.1548***	*0.0215*	0.1543***	*0.0215*	0.1538***	*0.0215*	0.1538***	*0.0216*	0.1534***	*0.0216*
logL	0.8129***	*0.0440*	0.7929***	*0.0451*	0.7854***	*0.0454*	0.7872***	*0.0453*	0.7929***	*0.0454*	0.7921***	*0.0453*	0.7975***	*0.0459*
Exper	-0.0772*	*0.0433*	-0.0829*	*0.0437*	-0.0808*	*0.0437*	-0.0843*	*0.0437*	-0.0799*	*0.0436*	-0.0826*	*0.0435*	-0.0824*	*0.0436*
ss11	0.2137***	*0.0778*	0.1872**	*0.0733*	0.3459***	*0.0868*	0.1006	*0.0807*	0.1883**	*0.0840*	0.1964**	*0.0950*	0.0404	*0.1071*
ss10	0.0636	*0.0508*	0.0073	*0.0573*	0.1255**	*0.0529*	-0.0107	*0.0485*	0.0021	*0.0512*	0.0106	*0.0701*	-0.0427	*0.0533*
ss01	0.1443	*0.0999*	0.1254	*0.1080*	0.1161	*0.0903*	0.2678***	*0.0883*	0.1242	*0.0886*	0.1412*	*0.0818*	0.1831**	*0.0789*
%Expor	-0.0814	*0.1661*	-0.1102	*0.1736*	-0.1087	*0.1736*	-0.1024	*0.1721*	-0.0989	*0.1706*	-0.1033	*0.1720*	-0.0890	*0.1749*
Expor	0.1330**	*0.0577*	0.1381**	*0.0578*	0.1387**	*0.0585*	0.1335**	*0.0574*	0.1376**	*0.0579*	0.1379**	*0.0579*	0.1349**	*0.0581*
age	0.0053***	*0.0016*	0.0051***	*0.0016*	0.0052***	*0.0016*	0.0050***	*0.0016*	0.0051***	*0.0016*	0.0052***	*0.0016*	0.0053***	*0.0016*
age*age	-3.06E-05***	*1.04E-05*	-3.01E-05***	*9.46E-06*	-2.98E-05***	*9.28E-06*	-2.91***	*9.62E-06*	-2.96E-05***	*9.68E-06*	-3,03E-05***	*9.56E-06*	-3.17-05***	*9.70E-06*
N	615		615		615		615		615		615		615	
R^2	0.7698		0.7735		0.7735		0.7743		0.7734		0.7734		0.774	
F value	0.0		0.2		0.8		2.13		0.32		0.15		0.77	
P value:	0.962		0.6515		0.3705		0.1446		0.5719		0.6963		0.3811	

NB: the dependent variable is the gross added value algorithm. Heteroskedasticity-robust standard errors (White procedure). Control variables: occupational structure, sectoral and regional dummies. ***, ** and * denote statistical significance of 1%, 5% and 10% respectively. F value: value of the statistical test of the null hypothesis of complementarity. (a) control variables were also introduced for the percentage of skilled workers in the other occupational groups.

The columns show the complementarity effect between technology and: skilled workers (column 1), managers (column 2), professionals (column 3), administrative and sales staff (column 4), floor managers and tradespersons (column 5), operators (column 6), and labourers (column 7).

Table 5 – Estimation of the augmented Cobb-Douglas production function taking into consideration the complementarity effect (Levinshon-Petrin).

	Model 1 (KH)		Model 2 (KHdire)[a]		Model 3 (KHprof)[a]		Model 4 (KHadm)[a]		Model 5 (KHenca)[a]		Model 6 (KHoper)[a]		Model 7 (KHpeon)[a]	
	Coef.	St. Dev.	Coef.	Est. Err.	Coef.	Est. Err.	Coef.	Est. Err.	Coef.	Est. Err.	Coef.	Est. Err.	Coef.	St. Dev.
logK														
logL	0.5500***	*0.0464*	0.5446***	*0.0472*	0.5386***	*0.0468*	0.5406***	*0.0471*	0.5435***	*0.0470*	0.5417***	*0.0473*	0.5463***	*0.0476*
Exper	-0.0581	*0.0360*	-0.0600*	*0.0362*	-0.0585	*0.0362*	-0.0606*	*0.0361*	-0.0589	*0.0364*	-0.0595	*0.0363*	-0.0603*	*0.0362*
ss11	0.1537***	*0.0589*	0.1361**	*0.0578*	0.2583***	*0.0642*	0.0952	*0.0631*	0.1216*	*0.0636*	0.1648**	*0.0740*	0.0774	*0.0815*
ss10	0.0210	*0.0421*	-0.0296	*0.0473*	0.0819*	*0.0445*	-0.0205	*0.0405*	-0.0184	*0.0431*	0.0076	*0.0604*	-0.0399	*0.0442*
ss01	0.1103	*0.0745*	0.0880	*0.0820*	0.1064	*0.0689*	0.1758**	*0.0702*	0.1291*	*0.0668*	0.1214**	*0.0620*	0.1354**	*0.0593*
%Expor	-0.2191*	*0.1294*	-0.2274*	*0.1341*	-0.2248*	*0.1331*	-0.2212*	*0.1331*	-0.2225*	*0.1330*	-0.2241*	*0.1345*	-0.2187	*0.1351*
Expor	0.0349	*0.0484*	0.0408	*0.0486*	0.0407	*0.0487*	0.0378	*0.0486*	0.0406	*0.0486*	0.0410	*0.0488*	0.0409	*0.0488*
age	0.0033**	*0.0014*	0.0032**	*0.0013*	0.00323**	*0.0014*	0.0032**	*0.0013*	0.0033**	*0.0013*	0.0032**	*0.0014*	0.0033**	*0.0014*
age*age	-2.13E-05***	*7.47E-06*	-2.08E-05***	*7.35E-06*	-2.09E-05***	*7.45E-06*	-2.09E-05***	*7.41E-06*	-2.16E-05***	*7.36E-06*	-2.12E-05***	*7.40E-06*	-2.18E-05***	*7.37E-06*
N	615		615		615		615		615		615		615	
R^2	0.8455		0.8475		0.8470		0.8471		0.8469		0.8469		0.8471	
F value	0.06		0.73		0.64		0.48		0.02		0.16		0.04	
P value	0.8024		0.3923		0.4251		0.4909		0.8937		0.6899		0.8343	

NB: the dependent variable is the gross added value algorithm. Heteroskedasticity-robust standard errors (White procedure). Control variables: occupational structure, sectoral and regional dummies. ***, ** and * denote statistical significance of 1%, 5% and 10% respectively. F value: value of the statistical test of the null hypothesis of complementarity. (a) control variables were also introduced for the percentage of skilled workers in the other occupational groups.

The columns show the complementarity effect between technology and: skilled workers (column 1), managers (column 2), professionals (column 3), administrative and sales staff (column 4), floor managers and tradespersons (column 5), operators (column 6), and labourers (column 7).