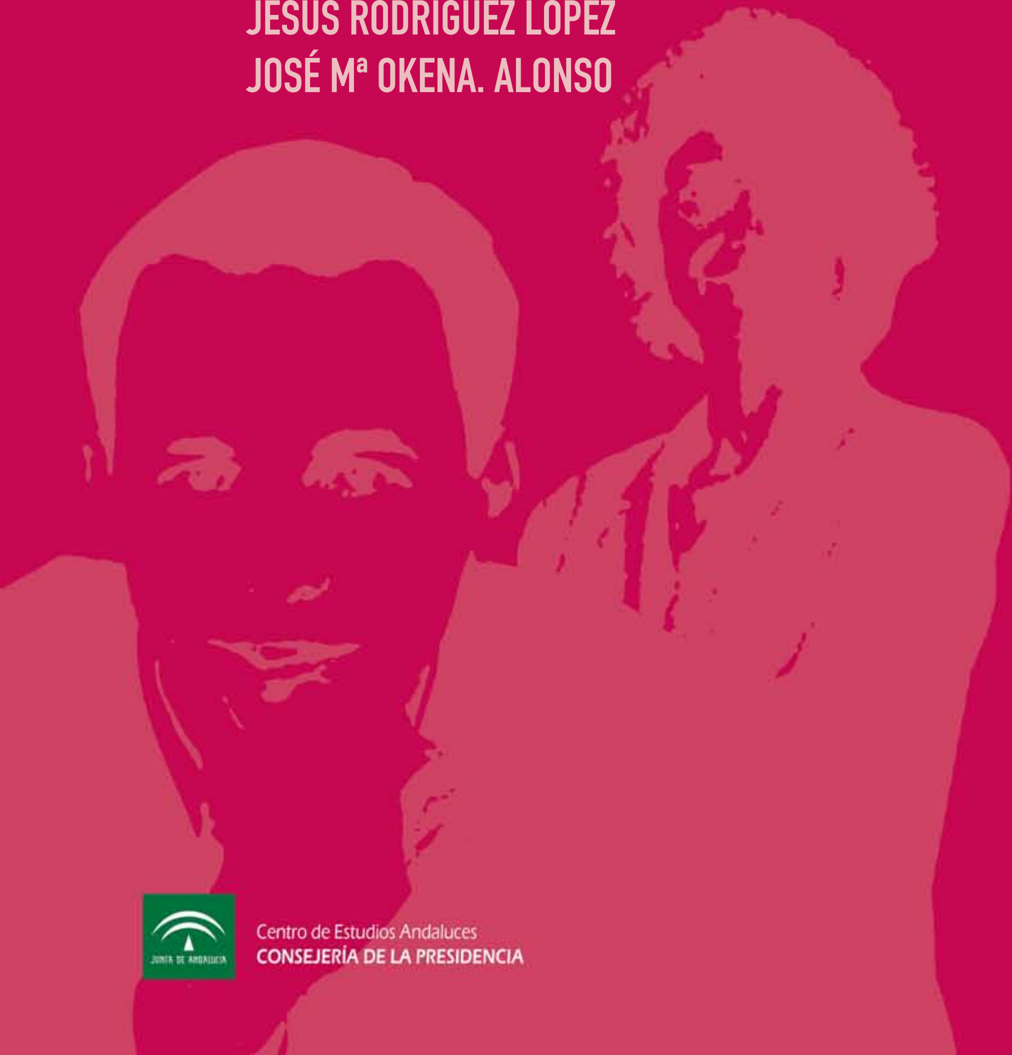
DOCUMENTO DE TRABAJO. E2008/ 13

# Labor demand and information technologies: Evidence for Spain, 1980-2005

MANUEL A. HIDALGO PÉREZ
JESÚS RODRÍGUEZ LÓPEZ
JOSÉ Mª OKENA. ALONSO



Centro de Estudios Andaluces
CONSEJERÍA DE LA PRESIDENCIA

Centro de Estudios Andaluces

El Centro de Estudios Andaluces es una entidad de carácter científico y cultural, sin ánimo de lucro, adscrita a la Consejería de la Presidencia de la Junta de Andalucía.
El objetivo esencial de esta institución es fomentar cuantitativa y cualitativamente una línea de estudios e investigaciones científicas que contribuyan a un más preciso y detallado conocimiento de Andalucía, y difundir sus resultados a través de varias líneas estratégicas.

El Centro de Estudios Andaluces desea generar un marco estable de relaciones con la comunidad científica e intelectual y con movimientos culturales en Andalucía desde el que crear verdaderos canales de comunicación para dar cobertura a las inquietudes intelectuales y culturales.

Las opiniones publicadas por los autores en esta colección son de su exclusiva responsabilidad


Depósito Legal: 7353-08

Centro de Estudios Andaluces
CONSEJERÍA DE LA PRESIDENCIA

E2008/13

# LABOR DEMAND AND INFORMATION TECHNOLOGIES: EVIDENCE FOR SPAIN, 1980-2005*

Manuel A. Hidalgo Pérez
Jesús Rodríguez López*
José María O.Kean Alonso

UPO

**Resumen**
Utilizando la base de datos EU KLEMS, se contrasta la hipótesis de complementariedad entre habilidad y capital en los distintos sectores productivos en España en el periodo 1980-2005. Se analizan tres tipos de trabajadores clasificados según su nivel de habilidad sea alto, medio o bajo. Los activos de capital se van a clasificar entre activos TIC (tecnologías de la información y la comunicación) y activos no-TIC. La adquisición y el uso de activos TIC son costosos pero ha ido disminuyendo en el periodo en consideración en términos relativos a otros activos y al factor trabajo. El principal resultado que se obtiene es que existe un grado de sustituibilidad entre los trabajadores y los activos TIC a medida que la habilidad del trabajador va aumentando. De hecho, los activos TIC son muy complementarios con los trabajadores de alta habilidad. A lo largo del periodo analizado, la fracción de trabajadores con habilidad media y alta ha crecido un 21% y un 12%, respectivamente, en detrimento de los trabajadores de baja habilidad. Después de descomponer estos cambios, se descubre que existe un ajuste dentro de los sectores más que un ajuste del trabajo entre sectores.

Clasificación JEL: E22, J24, J31, O33.
Palabras Clave: complementariedad capital-habilidad, TIC, elasticidad de sustitución.

Centro de Estudios Andaluces
CONSEJERÍA DE LA PRESIDENCIA

* Autor correspondencia: jrodlop@upo.es

**Abstract**

Using the EU KLEMS dataset we test the capital-skill complementarity hypothesis in a cross-section of sectors in Spain between 1980 and 2005. We analyze three groups of workers, who are classed according to skill level: high, medium and low. Capital assets have been broken down into ICT (information and communication technologies) assets and non-ICT assets. Acquisition and usage costs of ICT assets declined throughout the period studied, both in absolute terms and relative to the other capital assets and workers. Our principal finding is that the substitutability between workers and ICT assets falls as worker skill level rises. In fact, the ICT assets were strongly complement with highly skilled workers and were not substitutive with them. Throughout the period analyzed, the fraction of employed medium- and high-skill workers rose by 21% and 12%, respectively, to the disadvantage of low-skill workers. After decomposing these changes, we found that the latter were dominated by an adjustment within sectors more than by a composition effect or adjustment between sectors. These adjustments may be explained by reference to the estimated elasticities of substitution.

JEL codes: E22, J24, J31, O33.
Keywords: capital-skill complementarity, ICT, translog cost function, elasticity of substitution

# Labor Demand and Information Technologies: Evidence for Spain, 1980-2005[1]

Manuel A. Hidalgo Pérez    Jesús Rodríguez López
José María O'Kean Alonso
Universidad Pablo de Olavide

November 18, 2008

[1]The study forms part of the project "The impact of information systems on economic growth", financed by Microsoft Ibérica S.A. The authors would like to thank E. Alonso, M. Camacho, J.C. Conesa, M. Lindqvist, M. Mas, M. Saam, J. L. Torres and A. Villar for their insightful comments and suggestions. Matilde Mas helped to guide us in the management of the data. Corresponding author is Jesús Rodríguez-López: jrodlop@upo.es, Departamento de Economía, Métodos Cuantitativos e Historia Económica, Universidad Pablo de Olavide de Sevilla, Carretera de Utrera km. 1, 41013 Sevilla (Spain)

**Abstract**: Using the EU KLEMS dataset we test the capital-skill complementarity hypothesis in a cross-section of sectors in Spain between 1980 and 2005. We analyze three groups of workers, who are classed according to skill level: high, medium and low. Capital assets have been broken down into ICT (information and communication technologies) assets and non-ICT assets. Acquisition and usage costs of ICT assets declined throughout the period studied, both in absolute terms and relative to the other capital assets and workers. Our principal finding is that the substitutibility between workers and ICT assets falls as worker skill level rises. In fact, the ICT assets were strongly complement with highly skilled workers and were not substitutive with them. Throughout the period analyzed, the fraction of employed medium- and high-skill workers rose by 21% and 12%, respectively, to the disadvantage of low-skill workers. After decomposing these changes, we found that the latter were dominated by an ajustment within sectors more than by a composition effect or adjustment between sectors. These adjustments may be explained by reference to the estimated elasticities of substitution.

**JEL codes**: E22, J24, J31, O33.

Keywords: capital-skill complementarity, ICT, translog cost function, elasticity of substitution.

# 1 Introduction

Information and communication technologies (ICT), which have spread more rapidly and bolstered productivity more effectively than earlier technologies, have had a definite impact on the economy. In particular, numerous studies have pointed to the special role played by these technologies in the recovery of productivity growth since the mid-1990s in the United States and some European countries.

Such change implies an active adaptation process, as worker skills are changed to suit the new technologies and firms reorganize in new ways, because the complementarity and substituability relations (Griliches, 1969; Samaniego, 2006), replacing unqualified, unskilled workers with others whose training and experience is appropriate to the new context.

ICT-driven changes in the commercial realm have intensified the need for a skilled workforce, increasing both the demand for and the productivity of qualified workers and causing a rise in the relative wage of this group, especially in ICT-intensive countries such as the U.S., the U.K. and Sweden (Autor, 2002; Acemoglu, 2003). The fact that the price and cost of active ICT use has fallen steadily worldwide during the past two decades –more intensely if we take hedonic prices into account—suggest that a complementary relationship between assets and highly skilled workers represents the driving force behind such change. On the other hand, the weight of low-skill workers, who tend to concentrate in productive sectors where computers and information systems are little used, such as agriculture, construction and small business, is increasingly diminished.

These complementary or substitutive relationships can be measured using elasticity of substitution, which indicates how a firm changes its production plans in response to changes in the relative prices of the resources it uses. Estimating these elasticities helps to explain the sectoral adjustments in the composition of labor demand caused by price variation, in light of some basic principles regarding the maximization of profits.

In Spain, the composition of labor demand has changed as the use of ICT in the productive sectors has risen. Mas and Quesada (2006) have shown that human capital accumulation has been stronger in ICT-intensive sectors since 1980. The aim of this study is to estimate for Spain the elasticities of substitution between a number of productive resources, including workers of different skill levels and different capital assets (ICT and non-ICT). By combining the resources available in the Ivie-FBBVA and EU KLEMS databases, we can perform this estimation for a decomposition of 24 productive sectors between 1980 and 2005, comprising industrial and service activities. To aid our understanding of such fact, we differentiate between productive sectors that are ICT-intensive from those that are not, following the classification proposed by Mas and Quesada (2006). The results obtained confirm some of our a priori hypotheses. First, upon decomposing the changes in the composition of employed workers, we found that these changes were dominated by an adjustment *within* sectors, more than by a composition effect or by an adjustment *between* sectors. Throughout the period analyzed, the percentage of medium- and high-skill workers rose by 21% and 12%, respectively, to the detriment of low-skill workers, whose participation fell by 33%. Second, the substitutability between capital assets and workers fell as the skill level of the latter increased. Specifically, for low-skill workers, the elasticity of substitution was 2.76 with respect to communications equipment, 4.53 with respect to computer hardware, and 6.9 with respect to computer software and licenses. When applied to medium-skill workers, this elasticity was unitary in the three cases and became negative when applied to high-skill workers, indicating a complementary rather than a substitutive relationship. On the other hand, the elasticity of substitution with non-ICT capital assets was approximately 1.80 for all workers, regardless of skill level. Third, using a translog cost function allows us to estimate series of (non-constant) elasticities of substitution. The estimated elasticity series show a substitutability that is downward sloping for highly skilled workers, stable at about one for medium-skill workers, and upward sloping for low-skill workers. Fourth, and as expected, ICT assets were very complementary between each other and were substitutive with non-ICT assets.

From the perspective of industrial organization, these results provide a reasonable explanation of how technology has conditioned labor demand and human capital accumulation. In this vein, the result that a worker's substitutability decreases as her or his skill level increases accords with the results of similar research analyses for Spain and other countries.

From a macroeconomic analysis perspective, the result that elasticities of substitution are non-unitary and evolve unevenly, either increasing or decreasing, can serve as a guide when modeling a firm's production technology. The finding that a number of the elasticities are non-unitary explains why the participation of labor income in national income changed over the course of the period studied here, 1980 to 2005. Results of this type, using aggregate production function, can also be found in Duffy, Papageorgiou and Pérez (2004) and Papageorgiou and Chmelarova 2005), for a panel of countries. The framework of analysis can be compared to that of Falk and Koebel (2004), where they use yearly data for 35 sectors in Germany. Their paper is particularly focused to explore the relationship between ICT assets and workers with different skills.

This article is structured as follows. In Section 2 we study the relationship between ICT and human capital in Spain. Using simple techniques, we decompose the changes in the fraction of workers employed for each category in two sources: inter-sectoral and intra-sectoral changes. In Section 3, we propose a translog costs function to estimate the functions of factorial demand and elasticities of substitution. In Section 4 we show the evolution of prices relative to the factors considered in our cost function estimation, from which some of our observed facts derive. The econometric results of this estimation are presented in Section 5. In Section 6, we conclude. Transformations and the sources for the data used in this study are described in an appendix.

## 2 ICT, productivity and education

Studies by Jorgenson and Stiroh (2000), Jorgenson (2001) Colecchia and Schreyer (2002), Stiroh (2002), Daveri (2000), Timmer, Ypma and van Ark (2003, 2007) and Mas and Quesada (2006) have confirmed the following: (1) ICT asset accumulation in the European Union and U.S. economies over the past thirty years has risen more sharply than non-ICT asset accumulation; (2) productivity growth has increased with increased ICT use; (3) ICT represents the principal source of growth in countries where the use of this technology is most intense; (4) because ICT use in Spain is relatively low in comparison with the United States, the United Kindgom and Sweden, non-ICT capital has a greater impact on Spanish productivity growth than does ICT capital (Mas and Quesada (2006)).

The underlying explanation for this relationship between productivity growth and the intensity of ICT use lies with the technological progress embodied in these assets. For instance, the purchase of a computer represents not only the acquisition of a work tool, but also a means of technological accumulation, which can translate into greater productive efficiency and, thus, enhanced productivity. On the other hand, technological progress that incorporates traditional non-ICT assets, as compared with ICT ones, is very limited (Pakko, 2002 and 2005). A simple way to evaluate the implicit technological change of an asset is through the evolution of the hedonic price, which takes into account changes in the attributes and qualities associated with that asset (in this case, computer hardware).

The adoption of new technologies is not cost-free, but requires firms to implement changes with respect to organization and personnel and, in short, that they embrace new ways of doing business. Because this process of technological adaptation involves a high volume of resources, the advantages associated with ICT use tend to surface are not immediately evident.[1]

One effect of ICT use has been to eliminate a great many repetitive and tiring routine tasks, thereby freeing up large blocks of time which could then be filled with other tasks. As ICT use intensified during the 1990s, the aggregate production growth and labor productivity rates began to rise above the levels that they had displayed during the 1970s.

It should be noted that an integral part of this process has been the substitution of many existing workers, who had never used ICT on the job and were unprepared to do so, by new and better-trained ones more familiar with the new equipment. The latter have reaped the greatest benefits from the technological revolution, which spurred a rise in their wages. The same cannot be said of unskilled workers. Changes of this type have been observed for periods marked by other kinds of technological change. For example, Goldin and Katz (1998) have shown how the electrical revolution significantly altered the shape of labor demand in the United States in the early twentieth century (see also Berman, Bound and Griliches, 1994; Papageorgiou and Chmelarova 2005).

Mas and Quesada (2006) have classified the intensity of ICT use by studying the proportion of ICT assets represented in the overall capital stock of a sector, characterizing as ICT-intensive those sectors for which this proportion exceeded the average in 2004, the final year of their study. According to this criterion, eight productive sectors –listed in the first column of Table 1—may be classified as ICT-intensive. The other columns in Table 1 list data on the percentage of hours worked for three skill-level groups in each productive sector during the three central years of our sample –1985, 1995 and 2005— drawn from the EU KLEMS database. The EU KLEMS classification of the skilled levels is: *high* skill is for those workers with an university title or above; *medium* skill refers to secondary eduation; and *low* skilled is at most primary eduation or illiterate. These data show the evolution of the quality of the labor factor in each sector analyzed. In 1985, the percentage of low-skill workers was very high in all of sectors, especially in those classified as non-ICT intensive.

The mean proportion of highly skilled workers grew continually in all of the sectors studied, most notably in the ICT-intensive ones. For example, the observed mean for this characteristic practically doubled between 1985 and 2000, averaging 17.7% in 1985, 24.6% in 1995 and 33.6% in 2005. The most important changes can be seen precisely in the drastic reduction in the proportion of employed low-skill workers, which fell from 84.7% in 1985 to 54.5% in 2005. In general, the work employed in nearly all of the productive sectors was more highly skilled in 2005 than it was in 1985, with this change in the composition of labor being more marked in ICT-intensive sectors than in non-ICT intensive ones.

Nevertheless, it can be observed that the aggregate averages shown in Table 1 are also affected by changes in productive structure. Thus, the greater weight

[1] See Hornstein and Krusell (1996); Pakko (2002); Samaniego (2006). For an application of these ideas to the Spanish case, see Martínez, Rodríguez and Torres (2008).

of skilled labor-intensive activities sometimes increases the weight of skilled workers as a group. We proceed to decompose these weights in order to evaluate the dynamic behind this change. The aim is to learn how much of the weight variation for each group was caused by a change in the composition of productive activity which specifically favored that group, and how much of it resulted from the increased demand for such workers, regardless of the sector in which it occurred. To this end, we adapt the analysis of Berman, Bound and Griliches (1994) for the United States, in which the authors use occupational categories instead of skill levels, as we do here.

Let us consider three skill levels: high, medium and low, denoted respectively using the subindex $j \in \{h, m, \ell\}$, and let $h(j)$ be the proportion of hours worked by those of skill level $j$ during any given year. This proportion can be obtained as the weighted average of the participation of these workers in each of our sectors, that is

$$h(j) = \sum_{s=1}^{S} h(s,j)\, e(s), \tag{1}$$

for sectors $s = 1, \ldots, S$ and where

$$e(s) = \frac{\sum_{j\in\{h,m,\ell\}} \text{hours}(s,j)}{\sum_{s=1}^{S} \sum_{j\in\{h,m,\ell\}} \text{hours}(s,j)},$$

is the weight in employment terms (hours worked) of sector $s$, for any given year. At the same time, $h(s,j)$ is participation, in hours, of workers of skill level $j$ in sector $s$,

$$h(s,j) = \frac{\text{hours}(s,j)}{\sum_{i\in\{h,m,\ell\}} \text{hours}(s,i)}.$$

hours $(s,i)$ indicates the total number of hours worked in sector $s$ by workers of skill level $j \in \{h, m, \ell\}$. The weight of each sector is denoted by $0 < e(s) < 1$, in such a way that $\sum_{s=1}^{S} e(s) = 1$. At the same time, it can be shown that $\sum_{j\in\{h,m,\ell\}} h(j) = 1$.

On the basis of expression (1), the annual rise in participation $\Delta h(j)$ for a given two-year period can be decomposed as follows

$$\Delta h(j) = \sum_{s=1}^{S} \bar{h}(s,j)\, \Delta e(s) + \sum_{s=1}^{S} \Delta h(s,j)\, \bar{e}(s), \tag{2}$$

where the upper line reflects the mean value for the two years under comparison.

1. The first term, $\sum_{s=1}^{S} \bar{h}(s,j)\, \Delta e(s)$, represents the variation in the proportion of workers of skill level $j$ resulting from changes in sectoral structure or production specialization. We will call this component the *composition effect* or *between-group effect*.

2. The second term, $\sum_{s=1}^{S} \Delta h(s,j)\, \bar{e}(s)$, refers to the changes in the demand for workers of skill level $j$ within a given sector, regardless of the activity

taking place in other sectors. We call this component the *within-group effect.*

Starting from the expression (2) it is possible to learn which part of the change in the proportion $h(j)$ is associated with ICT usage intensity. To this end, we decompose the first observed effect as

$$\sum_{s=1}^{S} \bar{h}(s,j)\, \Delta e(s) = \sum_{s \in \mathcal{A}_1} \bar{h}(s,j)\, \Delta e(s) + \sum_{s \in \mathcal{A}_2} \bar{h}(s,j)\, \Delta e(s), \tag{3}$$

where $\mathcal{A}_1 = \{1, \ldots, \bar{s}\}$ groups together the eight ICT-intensive sectors and $\mathcal{A}_2 = \{\bar{s}+1, \ldots, S\}$ groups together the remaining sectors. The criterion for classifying sectors by the intensity of ICT usage follows the scheme set forth by Mas and Quesada (2006), which is reported in Table 1. The second intra-group effect is similarly decomposed.

Tables 2 and 3 show the results of this decomposition for high- and medium-skill workers, respectively. By default, the results for low-skill workers can be derived from these two categories, making it redundant to list them here. Table 2 shows incremental increases in the participation of highly skilled workers caused by the composition effect (column 1) and the intra-group effect (column 2), as well as the total increase (column (3) = (1) + (2)), the weight of each sectoral group in the total number of hours worked (column (4)) and, finally, the increases observed for each group, $\mathcal{A}_1$ and $\mathcal{A}_2$, (column (5)). The decomposition is given for the entire period and for five 5-year periods.

For the 1980-2005 period, the percentage of highly skilled workers employed in Spain rose by 12.16 percentage points. Of these, 8.68 points resulted from changes in intra-sectoral demand while the remaining 3.48 points resulted from changes in sectoral composition. Thus, 71.4% of the change during this two-year period was caused by intra-group changes (=8.68/12.16). The growth in the participation rate was very homogeneous throughout the period under study, averaging approximately 2.5%. With the exception of the first five-year period, the intra-group effect surpassed the inter-group effect. This result accords with the changes taking place in the Spanish economy between 1980 and 1985, during which an important country's industrial transformation took place. From 1996 to the present, nearly all of the changes in this rate can be explained by reference to intra-group changes.

With respect to the *between*-group differentiation between ICT-intensive sectors and non-ICT-intensive ones, despite the greater weight of non-intensive activities, the rise in the demand for highly skilled workers can be evenly attributed to both groups. The increase of the percentage of highly skilled workers employed was 16.6 points in the ICT-intensive sectors and 6.0 points in the non-ICT-intensive ones.Thus, these data imply that for the entire period under study, 6.6% of the overall 12.16% variation rate took place in the ICT-intensive sectors while the rest corresponds to non-ICT-intensive sectors. Of the 8.68% variation in the proportion of intra-group change, that attributable to ICT-intensive versus non-ICT- intensive sectors was roughly equal (4.12% versus 4.56%, respectively). These figures call into evidence the dynamic contribution of the ICT-intensive sectors to the employment of highly skilled workers throughout the period under study. Also, 2.53 of the 3.48 points attributed to the composition effect resulted from changes that worked in favor of the ICT-intensive sectors, versus 0.95 points resulting from changes that favored the non-ICT-intensive ones.

When we look at the 5-year intervals into which this 25-year period was divided, the important role played by ICT-intensive sectors in the evolution of the demand for skilled workers becomes clear. In short, this period witnessed the rise in widespread employment of highly skilled workers, regardless of ICT usage patterns.

Table 3 gives the salient results for workers in the medium-skill group. In the first place, the total variation for this group (21%) exceeds that observed for highly skilled workers (12.16%). This implies that the greatest adjustment in the composition of the employed workforce in Spain resulted from the greater employment of medium-skill workers. This fact accords with the strong increase in the number of job-seekers in this category since the late 1970s. The percentage of variation in low-skill workers was -33.2%, which implies that those who replaced them were largely of a medium skill level.

The changes in this proportion – $\Delta h\,(m)$ – almost exclusively responded to changes within each sector. In fact, sectoral adjustments contributed negatively to their variation, probably in favour of highly skilled workers. That is, while 22.6% of the overall change can be associated with direct substitutions of low-skill workers by medium-skill ones within each sector, the changes in sectoral composition also gave rise to a weak substitution rate of 1.6% of medium-skill workers by highly skilled ones.

The structure of this adjustment was very homogeneous throughout the established 5-year intervals, with the changes dominated by intra-group effects.

The contribution of the percentual variation was greater during the first three five-year periods, between 1980 and 1995, than it was during the final period, between 1996 and 2005.

In conclusion, the results mentioned above indicate that most of the changes observed here cannot be attributed to alterations in the productive structure of the Spanish economy, but rather to changes within the sectors studied. Such changes may have had multiple causes, as dictated by the substitutive and complementary relationships between different factors. In order to know how and why substitutions between workers of different skill levels occurred, we must consider the dynamic behind the sectors' adoption of these technologies, an econometric task that will be our focus in the next section.

[**Tables 1, 2 and 3 here**]

# 3 The demand for factors of production

In order to associate the changes in demand for workers of different skill levels to the variables that can explain these changes, we develop a specification using a trans-log cost function and Shepard's lemma in order to come up with a system of estimable equations. The resultant estimated parameters allow us to calculate the elasticities of substitution between various different resources involved in the productive process. Berman, Bound and Griliches (1993), Machin and Van Reenen (1998) and O'Mahoney, Robinson and Vecchi (2006), among others, have used this type of function for similar analytical ends.

We consider production to result from the combination of seven productive factors per sector and unit of time: workers of high, medium and low skill levels, indexed as $\{h, m, \ell\}$ respectively, three ICT capital assets (hardware, communications and software), and the non-ICT capital assets, indexed as $\{hard, com, soft, k\}$, respectively. Our data for these three worker sets, and for the production and cost fractions associated with each factor of production, comes from the EU KLEMS database. We use the capital and investment series in Spain estimated by Ivie-FBBVA.

Non-ICT capital is an aggregation of various items associated with traditional physical capital assets: non-residential structures and constructions, transportation equipment, metallic products, machines and mechanical equipment, and workshop and construction tools. We aggregated the items using a Törnqvist index, which takes into account variations in the relative prices (marginal products) of capital assets.

Suppose that the cost function of sector $s$ is approximated by the following second-order translog:

$$\ln C_{st} = \ln (p_{st})' [\eta_s t + \phi] + \frac{1}{2} \ln (p_{st})' B \ln (p_{st}), \tag{4}$$

where $p_{st}$ is the price vector of the seven productive factors under consideration at moment $t$. This vector denotes the wages of three categories of workers per sector and unit of time, $w_{ist}$ for $i \in \{h, m, \ell\}$,and the usage or rental costs of four capital assets, $R_{sjt}$ for $j \in \{hard, com, soft, k\}$

$$p_{st} = [w_{hst}, w_{mst}, w_{\ell st}, R_{hard,st}, R_{com,st}, R_{soft,st}, R_{kst}]'. \tag{5}$$

Time $t$ is explicitly included in cost function (4) and represents the change in cost not captured by the two capital assets or human capital. The vector that captures this effect is denoted by $\eta_s = \left[\eta_{hs}, \eta_{ms}, \eta_{\ell s}, \eta_{hard,s}, \eta_{com,s}, \eta_{soft,s}, \eta_{ks}\right]'$. On the other hand, $\phi$ is a parameter vector common to all productive sectors,

$$\phi = \left[\phi_h, \phi_m, \phi_\ell, \phi_{hard}, \phi_{com}, \phi_{soft}, \phi_k\right]'.$$

Finally, $B$ is a symmetrical matrix, so that

$$\beta_{ij} = B(i, j) = B(j, i) = \beta_{ji}, \tag{6}$$

with $i, j \in \{h, m, \ell, hard, com, soft, k\}$.

According to Shephard's lemma, the demand conditioned by any factor $i$ may be obtained through the partial derivative of the cost function with respect to the price of that factor, $\partial C_{st}/\partial p_{ist}$, where $p_{ist}$ is the $i-$th element of vector $p_{st}$

in (5), $i \in \{h, m, \ell, hard, com, soft, k\}$. Given that cost function (4) is specified in logarithms, if we multiply this derivative by $p_{ist}$ and divide it by $C_{st}$ we obtain that the cost share of factor $i$ can be defined as

$$\alpha_{ist} = \frac{p_{ist}}{C_{st}} \frac{\partial C_{st}}{\partial p_{ist}} = \frac{\partial \ln C_{st}}{\partial \ln p_{ist}}. \tag{7}$$

The variable $\alpha_{ist}$ measures the participation of a factor over total cost,

$$\sum_{i \in \{h,m,\ell\}} \alpha_{ist} + \sum_{i \in \{hard,com,soft,k\}} \alpha_{ist} = 1.$$

If we apply expression (7) to cost function (4), we obtain

$$\alpha_{ist} = \eta_{is} t + \beta_i + \sum_{j \in \{h,m,\ell\}} \beta_{ij} \ln w_{jst} + \sum_{j \in \{hard,com,soft,k\}} \beta_{ij} \ln R_{jst}, \tag{8}$$

for $i \in \{h, m, \ell, hard, com, soft, k\}$. We impose on this condition the following homogeneity condition of degree one of the cost function:

$$\mathbf{1}_{(1\times7)}\phi = 1, \tag{9}$$

$$\mathbf{1}_{(1\times7)}B = B\mathbf{1}_{(7\times1)} = 0. \tag{10}$$

where $\phi$ and $B$ are the matrixes of parameters defined in cost function (4), and $\mathbf{1}_{(7\times1)}$ is a vector of ones.

Bearing in mind the symmetry of matrix $B$, $\beta_{ij} = \beta_{ji}$, and the restrictions in (9) and (10), and taking first differences, the system of equations in (8) can be represented as follows:

$$\Delta\alpha_{hst} = \eta_{hs} - \sum_i \beta_{hi} \Delta \ln \left( \frac{w_{hst}}{p_{ist}} \right) + \varepsilon_{hst}, \tag{11}$$

$$\Delta\alpha_{mst} = \eta_{ms} - \sum_i \beta_{mi} \Delta \ln \left( \frac{w_{mst}}{p_{ist}} \right) + \varepsilon_{mst}, \tag{12}$$

$$\Delta\alpha_{\ell st} = \eta_{\ell s} - \sum_i \beta_{\ell i} \Delta \ln \left( \frac{w_{\ell st}}{p_{ist}} \right) + \varepsilon_{\ell st}, \tag{13}$$

$$\Delta\alpha_{hard,st} = \eta_{hard,s} - \sum_i \beta_{hard,i} \Delta \ln \left( \frac{R_{hard,st}}{p_{ist}} \right) + \varepsilon_{hard,st}, \tag{14}$$

$$\Delta\alpha_{com,st} = \eta_{com,s} - \sum_i \beta_{com,i} \Delta \ln \left( \frac{R_{com,st}}{p_{ist}} \right) + \varepsilon_{com,st}, \tag{15}$$

$$\Delta\alpha_{soft,st} = \eta_{soft,s} - \sum_i \beta_{soft,i} \Delta \ln \left( \frac{R_{soft,st}}{p_{ist}} \right) + \varepsilon_{soft,st}, \tag{16}$$

which includes an error term $\varepsilon_{ist}$, to be specified below. The equation for the non-ICT capital asset, $k$, is redundant, due to our assumptions of symmetry and the restrictions of (9) and (10). Note that the terms $\Delta \ln(p_{jst}/p_{ist})$ in equations (11) to (16) cancel for $i = j$. The coefficient $\eta_{is}$ can be interpreted as the effect of technological change on factor $i$ in sector $s$.[2] More specifically, $\eta_{is} + \varepsilon_{ist}$ represents the specific bias of each sector in factor $i$.

The partial elasticity of substitution for each factor pair can be obtained from the system estimations (11)-(16). We define the Allen-Uzawa partial elasticity of substitution between the two factors $i$ and $j$ as

$$\begin{aligned} ES(i,j)_{st} &= C_{st}\left(\frac{\partial^2 C_{st}}{\partial p_{ist}\partial p_{jst}}\right)\left(\frac{\partial C_{st}}{\partial p_{ist}}\frac{\partial C_{st}}{\partial p_{jst}}\right)^{-1} \\ &= 1 + \frac{\beta_{ij}}{\alpha_{ist}\alpha_{jst}}, \end{aligned} \tag{17}$$

with $i, j \in \{h, m, \ell, hard, com, soft, k\}$. The elasticity of substitution provides a way of measuring how a firm adjusts its production plans in response to changes in relative prices. When this elasticity approaches zero, $ES(i,j)_{st} \approx 0$, the factors of production are complementary, given that their relationship remains stable regardless of any changes in relative prices. When this elasticity is greater than or equal to one, the adjustment in the relative combination of two productive resources, $i$ and $j$, is proportionally greater than that of the change in the relative price. In this case, $ES(i,j)_{st} \geq 1$ factors $i$ and $j$ are said to be substitutive.

Parameter $\beta_{ij}$ in equation (12) is associated with the (logarithm of) the relative price of factors $i$ and $j$. If $\beta_{ij}$ is postive, the elasticity of substitution will be greater than one; that is, factors $i$ and $j$ will be substitutive. An increment in the relative price of factor $i$ with respect to factor $j$ would reduce the relative demand for the former, thereby also reducing its participation in costs. On the other hand, if $\beta_{ij}$ is negative, the elasticity of substitution will be less than unitary, so that the percentage increase in the relative wage will exceed the rise in the relative demand for this factor. As a result, their participation in overall costs would increase as a result of this complementarity. Finally, in the specific case in which $\beta_{ij} = 0$, the elasticity of substitution between factors $i$ and $j$ is one. In this way, the relative price increase of $i$ is counterbalanced by a proportional increase in the relative demand for $j$, so that the participation in costs $\alpha_{ist}$ remains unchanged. The latter case is similar to that of the Cobb-Douglas production function, which is a unitary and constant elasticity of substitution.

From expression (17) it can be seen that the elasticity of substitution varies from one moment to the next in accordance with the cost proportions $\alpha_{ist}$ and $\alpha_{jst}$. This equality allows us to estimate the elasticity of substitution for the entire period under consideration, once parameter $\beta_{ij}$ has been estimated.

[2] The parameter $\eta_{is}$ is is the marginal effect of time on the cost share of factor $i$. A positive value of it indicates an increase in the demand for this factor. Some authors interpret the effect of this parameter as the technological impact on factor demand (see Acemoglu, 2002, or Autor 2002, for an overview).

In order to specify the structure of the system of equations to be estimated, let us suppose that the error terms $\varepsilon_{ist}$ have the following structure:

$$\varepsilon_{ist} \sim iidN\left(0, \sigma_i^2\right). \tag{18}$$

Let us also assume that:

$$\begin{aligned} E\left(\varepsilon_{ist}\varepsilon_{is't}\right) &\neq 0, & (19)\\ E\left(\varepsilon_{ist}\varepsilon_{is't-\tau}\right) &= 0, & (20) \end{aligned}$$

for $s \neq s'$, and $i \in \{h, m, \ell, hard, com, soft, k\}$, for $\tau = 1, 2, ....$ On the other hand, let us suppose a certain correlation between the error terms of the two equations *within* each sector:

$$\begin{aligned} E\left(\varepsilon_{ist}\varepsilon_{jst}\right) &= \sigma_{ij}, & (21)\\ E\left(\varepsilon_{ist}\varepsilon_{jst-\tau}\right) &= 0, & (22) \end{aligned}$$

for $i \neq j$ and $i, j \in \{h, m, \ell, hard, com, soft, k\}$. This specification implies that equations (11)-(16) can be estimated using generalized least squares. We also correct for potential heteroskedasticity.

# 4 Wages and user costs of capital

The wage calculation for each of our three worker categories and for each branch of activity, obtained using data from the EU KLEMS database, is described in the appendix at the end of this study. For each category and sector, the nominal hourly wage was obtained by dividing the total wage costs by the total number of hours worked. These series provided by the EU KLEMS dataset are take account for the age of the workers (that can be a proxy for experience) and the sex.

The capital usage cost represents the rental price for each unit of capital asset over a given time period, and can be found by means of the following financial argument. Let $q_{jt-1}$ be the acquisition price of one unit of asset $j$ at time $t-1$. Let $R_{jt}$ be the rental price for this asset during any given time period. When the asset rental period has ended, the capital that remains once depreciation has been taken into account, $(1-\delta_j)$, can be sold at price $q_{jt}$, where $\delta_j$ is the depreciation rate for that asset. The monetary amount $q_{jt-1}$ invested in a unit of capital may be invested in a homogeneous financial asset which pays a nominal interest $i_t$. Using a log-linear version of this approximation, the calculation is finally performed using the expression

$$R_{jst} = q_{jst}\left(i_t + \delta_{js} - \Delta \ln q_{jst}\right), \tag{23}$$

$q_{jt}$ denotes the implicit deflator of investment in asset $j$.[3]

[3] Note that the user cost of capital, $R_{jt}$, is subindexed by the sector, $s$. This implies that the user cost of capital can change with the sector. The reason is that capital is an aggregate meassure that combines a portfolio of physical assets. This portfolio is different across sectors, and this produces different user costs of capital.

Nominal interest rate is denoted by $i_t = r_t + E_t(\pi_{t+1})$, where $r_t$ is the real interest rate and $E_t(\pi_{t+1})$ is the expected rate of inflation. Following Mas, Pérez and Uriel (2005), we use a constant value for the 4% true interest rate, $r_t = 0.04$. For the expected rate of inflation, we use a third-order centered moving average, where the rate of inflation $\pi_t$ is calculated using the percentage variation of the overall CPI.

The depreciation rate is calculated as the total depreciation ratio over the total capital fund. Finally, $\Delta \ln q_{jst} = \ln q_{jst} - \ln q_{jst-1}$, is the price variation rate for asset $j$.

Once an estimation for the price vector $p_{st}$ in (5), has been obtained, the calculation of the total cost of both labor and capital per unit of time and sector is expressed as

$$C_{st} = \sum_{i \in \{h,m,\ell\}} w_{ist} L_{ist} + \sum_{j \in \{hard,com,soft,k\}} R_{jst} K_{jst},$$

where $L_{ist}$ and $K_{jst}$ denote the quantities of work and capital employed, respectively. This expression can be used to calculate cost fractions $\alpha_{ist}$.

Graphics 1 and 2 show the temporary evolution of relative prices. For the sake of simplicity, wages have been aggregated for each of the three skill groups and for all sectors, including both ICT-intensive and non-ICT intensive ones (graph 1). These wages were obtained by considering the mean wage for each sector together with the fraction of hours worked for each activity group. At the same time, in order to simplify our presentation we aggregated over ICT and non-ICT, the two main items used here, to obtain capital usage cost (graph 2). Some interesting facts emerge when these graphs are used to interpret the results of the estimated elasticities of substitution, forthcoming in the following section.

Graphs 1.a and 1.b reflect two opposing tendencies, observable since at least 1995, in the relative wage of qualified workers with respect to medium- and low-skill ones. For all sectors, from the beginning of our study period until the mid-1990s the wage gap grew between highly skilled and medium-skill workers, $w_{hst}/w_{mst}$, (graph 1.a), while that between highly skilled and low-skill workers, $w_{hst}/w_{\ell st}$, decreased during the same period until the beginning of the 1990s (graph 1.b). This tendency appears not to apply to all of the sectors studied, since the relative wage of highly skilled and medium-skill workers rose steadily in ICT-intensive sectors during that time. In all sectors, the wage gap between medium- and low-skill workers, $w_{mst}/w_{\ell st}$, fell from the beginning of the study period until the early 1990s. From 1995 on, this relative wage appears to have remained stable (graph 1.e). From 1995 on, the position of highly skilled workers relative to medium- and low-skill ones fell as wages for the latter two groups began to evolve in parallel and the wage gap narrowed.

Hidalgo (2008) has found similar results for the evolution of relative wages in Spain for 1980, 1990 and 2000, using the wage data published in the Family Budget Surveys for 1980-81 and 1990-91 and the quarterly Continuous Family Budget Survey for 2000 and 2001. Despite he compares college versus the rest of workers, his results show similar patterns. For example the wage gap between both groups of workers slighltly grew in favor of college graduates during the 1980s, although it fell slightly during the 1990s.

Graphs 1.a- 1.c outline just one of a wide range of possible scenarios. Katz, Loveman and Blanchflower (1995), Gottschalk and Smeeding (1997), Gottschalk and Joyce (1998) and Acemoglu (2003) provide empirical evidence for a broad cluster of countries where the principal characteristic is great diversity in the evolution of the relative wage of skilled and unskilled workers. Thus, the relative wage for both of these groups rose in some countries (such as the United States and the United Kingdom) while it fell in others (such as Belgium and Sweden) and remained constant in still others (such as Germany). All of these cases were established with reference to time periods similar to the one studied here. As Acemoglu (2003) points out, different patterns of change in the relative supply and demand for skilled workers may account for this diversity.[4] For example, in countries where a strong increase in the supply of skilled workers was observed, the relative wage either fell or remained stable. For the Spanish case, although we can detect a clear rise in firms' demand for skilled workers, the changes in the evolution of the wage gap between workers of different skill levels has principally been governed by changes in relative supply (Hidalgo, 2008): the significant growth in the supply of workers of average education, which was far greater than that of the other groups, explains why the wage gap between university graduates and those in this group (i.e. $w_{hst}/w_{mst}$) grew during the 1980s; the greater growth in university graduates with respect to workers of other educational levels in the Spanish labor market from the early 1990s would explain the fall in relative wages vis-a-vis that of other workers. This explanation fits well with the data shown in graphs 1.a, 1.c and 1.e.

When we compare wages with the costs of using ICT capital equipment, the cost of the latter fell in comparison with that of the three worker groups we studied, $w_{ist}/R_{tic,t}$, for $i \in \{h, m, \ell\}$ (graphs 1.d, 1.f and 1.h). In this case, if the ICT capital and the labor input were substitutive, the behavior of the relative prices would imply a substitution of the latter by the former.

Finally, graph 2 shows that the price of ICT capital fell in relation to non-ICT capital; if both are substitutive, therefore, this tendency must have caused the former to replace the latter.

[**Figures 1 and 2 here**]

# 5 Results

System (11)-(16) was estimated three times: (i) for the 24 productive sectors analyzed here (excluding the primary sector), (ii) for the 8 sectors classed as ICT-intensive, and (iii) for the remaining 16, non-ICT-intensive sectors. The results for system parameters are listed in columns I, II and III of Table 4, and

[4] Alternative explanations can be related to different labor market institutions, the influence of labor unions, or the globalization of economies (Acemoglu, 2003).

those for elasticities of substitution are given in Table 5.[5] These elasticities represent the weighted average of all of the sectors analyzed during the defined study period, 1980-2005. Standard deviations have been calculated following Anderson and Thursby (1986), to contrast the null hypothesis with an elasticity of substitution that is equal to one ($H_0 : E(i, j) = 1$).

On the basis of these estimates, we reach the following conclusions. First, classifying our data by sector did not produce significant differences in the parameters we estimated; although there are slightly differences between the values estimated, we obtain similar signs for $\beta's$, as is shown in columns I, II and III of Table 4. Given that cost fractions $\alpha_{ist}$ were used to calculate the elasticities listed in Table 5, as the value of these fractions changes, we do find that these elasticities are different depending on the usage intensity of the ICT.

Second, the substitutability between ICT assets and labor decreases as the worker's skill level rises. Highly skilled workers and ICT assets were complementary in each and all of the sectors analyzed, as shown by the negative $\beta_{hj} < 0$ for $j = hard, com, soft$, but they are substitutive for non-ICT capital assets, $\beta_{h,k} > 0$. All of these estimators are statistically significant. With regard to the relationship between highly skilled workers and medium- or low-skill workers, it is substitutive. Since the estimator is not statistically significant for high- and medium-skill workers, we cannot reject our null hypothesis that the substitution elasticity is unitary. By contrast, the estimator is significant, $\beta_{h,\ell} = 0.052$, for highly skilled and low-skill workers, and the elasticity of substitution is greater than 1.

Third, most of the parameters associated with medium-skill workers are insignificant, which means that we cannot reject our null hypothesis that the elasticity of substitution is unitary. Only the value of the substitution elasticity between these workers and the non-ICT assets, $ES(m, k)$ –about 1.8- deviates from 1 (Table 5). In the non-ICT-intensive sectors, there appears to be a certain degree of complementarity between these workers and ICT hardware and software assets ($\beta_{m,hard} = -0.005$, $\beta_{m,soft} = -0.006$).

Fourth, low-skill workers are substitutive of all other factors studied. The estimated parameters and elasticities are statistically significant in every case, regardless of sector. This result, together with the evolution of relative wages shown in graph 1, explains why throughout our study period the employment rate for this type of worker fluctuated more than that of any other group (between 1980 and 2005, the fraction of low-skill workers fell by 33%).

Fifth, ICT capital assets are complementary amongst themselves and substitutive of traditional capital assets. Especially since the 1970s, the supply of skilled workers in Spain has grown, thanks largely to a rise in secondary education. More specifically, a sharp increase in the relative supply of educated workers, particularly high school graduates and college graduates during 1980s and 1990s, respectively, caused a drop in the relative wage of low-skill workers. This relative increase in the price of low-skill labor coincided with the

[5] The elasticities have been separately calculated for all sectors, both intensive and non-intensive ones. Average cost shares, $\alpha_{ist}$, are used to weight expression (17).

substitution and complementary relationships found here, inducing a number of adjustments within the ICT-intensive and non-ICT-intensive sectors. Thus, the complementarity between ICT capital and skilled labor and the lower price of such capital relative to that of non-ICT capital encouraged the accumulation of skilled workers in ICT-intensive sectors. This accumulation put unskilled workers –who were highly substitutable with both ICT capital and skilled workers- at a disadvantage.

These results accord with those found for countries other than Spain. For example, Krusell, Ohanian, Ríos-Rull and Violante (2000) have estimated the elasticities of substitution between capital equipment and skilled and unskilled labor for the United States between 1963 and 1992. They found an elasticity of substitution of 0.67 for skilled labor and capital equipment, and one of 1.67 for unskilled labor and capital equipment. Using the same data, Polgreen and Silos (2008) calculated the Allen-Uzawa partial elasticities for equipment capital and skilled and unskilled labor, respectively, as -1.20 and 1.79. For comparative purposes, these authors re-estimated these elasticities using capital price series other than those used by Krussel et al. Using NIPA deflators, they thus obtained partial elasticities between capital equipment and skilled and unskilled work of 0.64 and 9.88, respectively. When the data employed in Greenwood Herkowitz and Krussell (1997) were used, they found these elasticities to be 1.01 and 12.08, respectively.

Other results for countries other than Spain show similarities and differences with those obtained in this study. For instance, Falk and Koebel (2004) study the case of Germany between 1974 and 1998, and find similar results to ours, although a clear evidence of the substituibility between unskilled workers and ICT assets is only found for the non-manufacturing sectors. A second example with similar results is the work of O'Mahony, Robinson and Vecchi (2006) for the U.S., the U.K., France and Germany, using a translog framework. Biscourp et al (2002) found a partial elasticity of -1.7 between skilled workers and computers, and other 3.5 for unskilled workers with respect to the same capital, for France during the 1994-1997 period. Finally, in various sectors for Japan between 1980 and 1998, Nishimura et. al. (2002) have estimated partial substitution elasticities between ICT and young skilled and unskilled workers. Their results vary within intervals ranging from -22.26 to -0.58 for the case of skilled workers and between 1.32 and 10.44 for unskilled ones.

To end this survey of our results, graphs 3, 4 and 5 show the evolution of elasticities over time. In each of these graphs a dotted line has been inserted at value one, as a reference of the statistical significance. The shadowed area is a 95% confidence band, following the estimate by Anderson and Thursby (1986). Statistically significant estimations can be found where the band deviates from the dotted line. Graphs 3, 4 and 5 have a similar profile.

The downward-sloping substitution elasticities for workers with high and medium skill levels ($ES\,(h,m)$, graphs 3.1, 4.1 and 5.1) and for highly skilled workers and non-ICT assets ($ES\,(h,k)$ graphs 3.6, 4.6 and 5.6) indicate a fall in substitutability with respect to these factors. Such workers are complementary with ICTs, for which the values of this series appear to approach zero gradually going from negative values towards zero; that is, they display perfect complementarity as described in a Leontieff technology. In the case of medium-skill workers, where we have not been able to reject the null hypothesis of unitary elasticity, the series have a flat profile and the 95% confidence band reaches unity in all cases. Finally, for highly skilled workers the series is upward-sloping, especially $ES\,(\ell, hard)$ in graphs 3.12, 4.12 and 5.12, $ES\,(\ell, com)$ in graphs 3.13, 4.13 and 5.13 and $ES\,(\ell, k)$ in graphs 3.15, 4.15 and 5.15. This indicates that their substitutability rose over the course of our study period. In short, substitutability fell for those highly skilled workers, remained stable for medium-skill ones, and rose for low-skill ones.

Graphs 1.b and 1.e call into evidence narrowing of the wage gap between high- and low-skill workers and medium- and low-skill workers, $w_{hst}/w_{\ell st}$ and $w_{mst}/w_{\ell st}$, respectively. On the other hand, the relative wage of high- and medium-skill workers, $w_{hst}/w_{mst}$, has been decreasing since the mid-1990s in these non-ICT-intensive sectors (graph 1.a). The narrowing of the wage gaps has allowed medium- and high-skill workers to substitute low-skill ones in the sectors where ICT usage is relatively low. Given the reduction in the relative usage cost between ICT capital and non-ICT capital (graph 2), had there been a widening of the wage gap, the non-ICT-intensive sectors would have substituted high-skill workers for low-skill ones.

The confidence bands estimated for the substitution elatisticities between the different capital assets discussed above, both ICT and non-ICT ones, do not coincide with the unitary dotted line. These series do, however, display a relatively stable profile and this confirms the relationships of complementarity and substitution described in Tables 4 and 5, above.

Finally, when we have estimated the system of equations (11) to (16) splitting the sample for the time intervals 1980-1990 and 1991-2005, the estimated parameters $\beta' s$ as well as the elasticities of substitution do not suffer mentionable alterations.[6] The previous conclusions are therefore robust to the selection of the sample period.

[**Tables 4 and 5 and figures 3, 4 and 5 here**]

## 6 Conclusions

The combination of productive resources used by a given firm is determined by relationships of complementarity or substitutability. The aim of this study has been to estimate for Spain the elasticities of substitution between a wide range of productive resources, including workers of different skill levels (high, medium and low) and different types of capital assets (ICT and non-ICT ones). The combined use of available sources of data on capital and work has allowed us to estimate these elasticities for 24 productive sectors from 1980 to 2005. In this way, we have tried to evaluate the impact of ICT diffusion on labor demand in these productive sectors. While most Spanish sectors show a non-intensive

[6] These results, not reported here, can be seen upon request to the authors.

use of ICT capital equipment, the data for the few sectors with high rates of ICT usage is more positive with respect to productivity and the accumulation of human capital than that for other sectors (Mas and Quesada, 2006). As pointed out by Gust and Márquez (2004), some labour market regulatory practices have slowed the ICT adoption in a number of industrial countries, including Spain.

Our results can be summed up in three points. First, the substitutability between capital assets falls as worker skill level rises; second, the estimated elasticities suggest that ICT equipment and highly skilled workers are complementary; and third, the estimated elasticity series allow us to conclude that substitutability is downward-sloping for highly skilled workers, stable at about one for medium-skill workers and upward-sloping for low-skill workers.

Given the evaluation of relative prices, these estimations provide a reasonable explanation of the dynamic behind the demand for workers in specific skill-level groups. The process of human capital accumulation of the eight ICT-intensive sectors is the result of the complementarity observed here between highly skilled workers and ICT equipment and the evolution of relative prices. Low-skill workers were strongly substitutive with the capital assets we considered. The price of both kinds of assets has fallen in Spain and worldwide since the mid-1970s, changing the shape of the labor market such that the job opportunities for low-skill workers are becoming less and less abundant. As a consequence, the lower the worker's skill level, the more marked has been the adjustment in the demand for workers of that level and the greater the intensity of ICT usage. This substitutive tendency will continue to grow more striking as ICT usage gradually spreads into the other productive sectors.

Finally, and in the vein of this argument, it must be noted that the process of ICT diffusion may have been determined by the high adjustment or installation costs associated with these technologies. Such costs fall as ICT usage rises. During the 1980s, sectors currently considered to be ICT-intensive invested heavily in the new technologies; they have already paid for the costs of the adjustment process, which required that they make important organizational changes (both horizontal and vertical). In other words, certain productive sectors which the data now describe as being non-ICT intensive may, in fact, become ICT-intensive once their installation costs have been paid off. In this way, the technological and work relationships within these sectors may become assimilated into those of the existing ICT-intensive ones. The secret of how the labor work will respond to this adaptive process lies in how the Spanish educational system will adapt its contents to ICT and to the rigors of the marketplace.

Nevertheless, academic rigor obliges us to note that these results should not be interpreted as predictions. In the future, production of ICT may be adapted to fit the needs of less-skilled users and not the other way around, as has been the case until now. In such a context, technological relationships could shift from being complementary to being substitutive. Our goal has been to explain the unfolding of events between 1980 and 2005, using sample data that falls into that date range. However, there is no indication that these estimations will remain stable over time.

# References


[1] Acemoglu, D.: Technical Change, Inequality, and the Labor Market". *Journal of Economic Literature* 2002; 40, 7-72.

[2] Acemoglu, D.: Cross-Country Inequality Trends". *Economic Journal* 2003; 113, 121-149.

[3] Anderson and Thursby: Confidence Intervals for Elasticity Estimators in Translog Models. *The Review of Economics and Statistics* 1986; 68(4); 647-656.

[4] Autor, D.: Skill Biased Technical Change and Rising Inequality: What is the Evidence? What are the Alternatives? Mimeograph, 2002:

[5] Berman, E. and Bound, J. and Griliches, Z.: Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures. *The Quarterly Journal of Economics* 1994; 109; 367-97.

[6] Biscourp, P; Crépon, B.; Heckel, T. and N. Riedinger: How do firms respond to cheaper computers? Microeconometric evidence for France based on a production function approach. Série des documents de travail de la Direction des Etudes et Synthèses Économiques, Institut National De La Statistique Et Des Études Économiques, Paris, (2002).

[7] Colecchia, A. and P. Schreyer: ICT investment and economic growth in the 1990's: Is the United States a unique case? A comparative study of nine OECD countries. *Review of Economic Dynamics* 2002; April 5(2); 408-442.

[8] Daveri, F.: Is Growth an ICT-Story in Europe Too? Università Bocconi, IGIER, Working paper, n$^o$ 168 (2000).

[9] Duffy, J., C. Papageorgiou and F. Pérez-Sebastian: Capital Skill Complementarity? Evidence from a Panel of Countries?. *The Review of Economics and Statistics* 2004; 86(1); 327-344.

[10] Falk, M., and B.M. Koebel: The impact of office machinery, and computer capital on the demand for heterogeneous labour. *Labour Economics* 2004; 11; 99–117.

[11] Freeman, R. and L. F. Katz: Differences and Changes in Wage Structures. Chapter Introduction and Summary, University of Chicago Press, Freeman, Richard and Lawernce F. Katz (Eds); 1995.

[12] Goldin, C. and L. F. Katz: The Origins of Technology-Skill Complementarity. *Quarterly Journal of Economics* 1998; 113; 693-732.

[13] Gottschalk, P., and M. Joyce: Cross-National Differences In The Rise In Earnings Inequality: Market And Institutional Factors. *The Review of Economics and Statistics* 1998; 80(4); 489-502.

[14] Gottschalk, P., and T. M. Smeeding: Cross-National Comparasions of Earnings and Income Inequality. *Journal of Economic Literature* 1997; 35; 633-687.

[15] Greenwood, J; Hercowitz, Z. and P. Krusell: Long-Run Implications of Investment-Specific Technological Change. *American Economic Review* 1997; 87(3); 342-362.

[16] Griliches, Z.: Capital-Skill Complementarity. *The Review of Economics and Statistics* 1969; 51(4); 465-68.

[17] Gust, C. and J. Márquez: International comparisons of productivity growth: the role of information technology and regulatory practices. *Labour Economics* 2004; 11; 33– 58.

[18] Hidalgo, M.A.: A Demand-Supply Analysis of the Spanish Education Wage Premium in the 1980s and 1990s. Universidad Pablo de Olavide, Working Paper 08.01 (2008).

[19] Hornstein, A., Krusell, P.: Can Technology Improvements Cause Productivity Slowdowns? In: Bernanke, B., Rotemberg, J. (Eds.), *NBER Macroeconomics Annual* 1996; 11; 209-259.

[20] Jorgenson, D. W.: Information Technology and the US Economy. *American Economic Review* 2001; 91(1), 1-32.

[21] Jorgenson, D. W. and Stiroh, K. J.: Raising the Speed Limit: U.S. Economic Growth in the Information Age. *Brooking Papers on Economic Activity* 2000; 1, 125-211.

[22] Katz, L., G. Loveman, and D. Blanchflower: Differences and Changes in Wage Structureschap. A Comparison of Changes in the Structure of Wages in Four OECD Countries. University of Chicago Press, Chicago, Freeman, Richard and Lawernce F. Katz ed (1995).

[23] Krusell, P., Ohanian, L., Rios-Rull, V. and G. Violante: Capital Skill Complementary and Inequality: A Macroeconomic Analysis. *Econometrica* (2000); 68(5); 1029-1053.

[24] Machin, S and J. Van Reenen: Technology and Changes in Skill Structure: Evidence from Seven OECD Countries. *The Quarterly Journal of Economics* 1998; 113(4) 1215-1244.

[25] Mas, M., Pérez, F. and Uriel, E.: El stock y los servicios de capital en España. Nueva Metodología (1964-2002). Fundación BBVA, Bilbao; 2005.

[26] Mas, M., Pérez, F. and Uriel, E.: El stock y los servicios de capital en España, 1964-2005. Fundación BBVA, Bilbao; 2007.

[27] Mas, M. and J. Quesada: "The Role of ICT in the Spanish Productivity Slowdown. Documentos de Trabajo de la Fundación BBVA 2006-5.

[28] Martínez, D.; Rodríguez, J and J.L. Torres: The productivity paradox and the new economy: The Spanish case. *Journal of Macroeconomics* 2008; 30(4); 1569-1586.

[29] Nishimura, K.G.; Minetaki, K.; Shirai, M. and F. Kurokawa: Effects of Information Technology and Anging Work Force on Labor Demand and Technological Progress in Japanese Industries: 1980-1998. CIRJE F-Series CIRJE-F-145, CIRJE, Faculty of Economics, University of Tokyo (2002).

[30] O'Mahony, M., C. Robinson and M. Vecchi: The Impact of ICT on the Demand for Skilled Labour: A Cross-Country Comparison. Mimeo; 2006.

[31] Pakko, M.R.: What Happens When the Technology Growth Trend Changes? Transition Dynamics, Capital Growth, and the New Economy. *Review of Economic Dynamics* 2002; 5(2); 376-407.

[32] Pakko, M.R.: Changing technology trends, transition dynamics and growth accounting. Working Papers 2000-014, Federal Reserve Bank of St. Louis; 2005.

[33] Papageorgiou, C. and V. Chmelarova: Nonlinearities in Capital–Skill Complementarity. *Journal of Economic Growth* 2005; 10; 59–89.

[34] Polgreen, L. and P. Silos: Capital-Skill Complementarity and Inequality: A Sensitivity Analysis. *Review of Economic Dynamics* 2008; 11(2), 302-313.

[35] Samaniego, R.M.: Organizational capital, technology adoption and the productivity slowdown. *Journal of Monetary Economics* 2006; 53; 1555–1569.

[36] Stiroh, K: "Information technology and U.S. productivity revival: What do the industry data say? *American Economic Review* 2002; 92(5); 1559-1576.

[37] Timmer, M. P., G. Ypma and B. van Ark: "IT in the European Union: Driving Productivity Divergence? GGDC Research Memorandum GD-67; 2003.

[38] Timmer, M. P., M. O'Mahoney and B. van Ark: "EU KLEMS Growth and Productivity Accounts: An Overview; 2007.

# A Datos

**EU KLEMS**. We use data samples for Spain taken from the EU KLEMS database[7]. This database contains data series from 1980 to 2008 for 29 productive sectors with economic variables that are relevant to the study of production, work and capital, the transformation of which will be explained below.

[7] For a description of this methodology, see Timmer, O'Mahony and van Ark (2007), and van Ark, O'Mahony and Ypma (2007). The data base site is `http://www.euklems.net/`

We will use the same notations referred to in this database for the calculation and transformation of our variables. Let $h_{ist}$ be the total number of hours work by workers of skill level $i \in \{h, m.\ell\}$ in sector $s$, calculated as

$$h_{hst} = H\_HS_{st} \times H\_EMP_{st}, \quad (24)$$
$$h_{mst} = H\_MS_{st} \times H\_EMP_{st}, \quad (25)$$
$$h_{\ell st} = H\_LS_{st} \times H\_EMP_{st}, \quad (26)$$

where $H\_HS_{st}$, $H\_MS_{st}$, $H\_LS_{st}$, are the proportion of hours worked by workers of high, medium and low skill levels, respectively. $H\_EMP_{st}$ is the total number of hours worked by hired employees, and $EMP_{st}$ represents the total number of hired employees in sector $s$ at moment $t$.

The fraction of income to work for workers of skill level $i \in \{h, m, \ell\}$, is directly calculated in the EU KLEMS database as LABHS, LABMS y LABLS, respectively, LABHS + LABMS + LABLS = 1.

Total labor incomes measured in current euro values, that include self-employment wages and payments, are designated by the variable LAB. Fractions of the earned income used to pay ICT and non-ICT capital have been calculated as described in Section 3.

The wage paid to a worker of skill level $i \in \{h, m, \ell\}$ in sector $s$ at moment $t$, $w_{ist}$, is calculated as follows:

$$w_{hst} = \frac{LABHS_{st} \times LAB_{st}}{h_{ast}}, \quad (27)$$
$$w_{mst} = \frac{LABMS_{st} \times LAB_{st}}{h_{mst}}, \quad (28)$$
$$w_{\ell st} = \frac{LABLS_{st} \times LAB_{st}}{h_{\ell st}}, \quad (29)$$

where $LAB_{st}$ is the total labor compensation, in millions of euros.

**Ivie-FBBVA**. Capital series are drawn from the database compiled by Mas, Pérez and Uriel (2005, 2007), which divides the data into eighteen physical capital assets for 1964-2005.[8] Non-ICT captial assets have been grouped into three categories: non-residential constructions and buildings, elements of transportation, and machinery and other equipment. ICT capital series have also been grouped into three categories: computers and office equipment, program and software licenses. These ICT series have been deflated using the hedonic prices of the BEA (see Mas, Pérez and Uriel, 2005, pp. 71 and 168-173). The database also offers real and nominal investment series for the different assets.

[8] `http://www.fbbva.es/`

## B Tables

**Table 1: Percentage of hours worked according to skill**

| | 1985 | | | 1995 | | | 2005 | | |
|---|---|---|---|---|---|---|---|---|---|
| | High | Medium | Low | High | Medium | Low | High | Medium | Low |
| **Intensive ICT users** | 17.7 | 17.8 | 64.5 | 24.6 | 28.9 | 46.5 | 33.6 | 35.5 | 30.8 |
| Pulp, paper, printing & publish. | 5.8 | 13.0 | 81.2 | 8.9 | 24.8 | 66.3 | 15.0 | 33.9 | 51.1 |
| Energy and water | 12.5 | 18.3 | 69.2 | 19.6 | 32.2 | 48.2 | 33.0 | 37.8 | 29.2 |
| Electric, electronic, optic equip. | 8.9 | 22.1 | 69.0 | 15.6 | 37.8 | 46.6 | 24.1 | 45.2 | 30.7 |
| Transport and communication | 6.0 | 14.1 | 79.9 | 9.5 | 25.7 | 64.7 | 17.0 | 37.8 | 45.3 |
| Financial intermediation | 15.5 | 35.8 | 48.7 | 29.8 | 44.5 | 25.7 | 50.3 | 39.0 | 10.6 |
| Business services | 25.1 | 22.1 | 52.8 | 30.4 | 29.1 | 40.5 | 39.8 | 32.1 | 28.2 |
| Private health & social services | 43.6 | 12.4 | 44.0 | 46.3 | 25.0 | 28.7 | 49.0 | 34.3 | 16.7 |
| Other community services | 7.2 | 14.0 | 78.8 | 14.1 | 26.3 | 59.6 | 24.2 | 36.9 | 38.9 |
| **Non-Intensive ICT users** | 7.5 | 7.8 | 84.7 | 10.7 | 18.6 | 70.7 | 15.3 | 30.2 | 54.5 |
| Food, drink and tobacco | 3.3 | 8.3 | 88.5 | 5.7 | 18.0 | 76.3 | 11.1 | 29.1 | 59.8 |
| Textiles, leather and footwear | 2.8 | 7.1 | 90.1 | 3.3 | 13.8 | 82.9 | 6.4 | 25.8 | 67.8 |
| Wood and crok products | 5.8 | 13.0 | 81.2 | 8.9 | 24.8 | 66.3 | 15.0 | 33.9 | 51.1 |
| Oil refin., coke & nuclear fuel | 5.8 | 13.0 | 81.2 | 8.9 | 24.8 | 66.3 | 15.0 | 33.9 | 51.1 |
| Chemicals | 5.8 | 13.0 | 81.2 | 8.9 | 24.8 | 66.3 | 15.0 | 33.9 | 51.1 |
| Rubber & plastics | 5.8 | 13.0 | 81.2 | 8.9 | 24.8 | 66.3 | 15.0 | 33.9 | 51.1 |
| Other non-metallic mineral | 5.8 | 13.0 | 81.2 | 8.9 | 24.8 | 66.3 | 15.0 | 33.9 | 51.1 |
| Fabricated metal products | 5.8 | 13.0 | 81.2 | 8.9 | 24.8 | 66.3 | 15.0 | 33.9 | 51.1 |
| Machinery and mechanical eq. | 7.4 | 20.5 | 72.1 | 7.4 | 32.9 | 59.7 | 13.6 | 46.5 | 39.9 |
| Transport equip. manufact. | 4.2 | 14.2 | 81.6 | 8.2 | 29.6 | 62.2 | 17.0 | 41.7 | 41.3 |
| Miscellaneous manufact. | 2.9 | 7.7 | 89.5 | 2.8 | 14.5 | 82.7 | 7.6 | 28.9 | 63.6 |
| Construction | 3.7 | 5.3 | 91.0 | 4.3 | 15.3 | 80.4 | 7.7 | 25.1 | 67.2 |
| Wholesale & retail trade; Repairs | 3.5 | 11.3 | 85.2 | 6.5 | 25.0 | 68.5 | 12.1 | 38.7 | 49.2 |
| Hotels and catering | 1.6 | 6.6 | 91.8 | 3.4 | 17.5 | 79.1 | 9.1 | 34.5 | 56.4 |
| Real estate | 25.1 | 22.1 | 52.8 | 30.4 | 29.1 | 40.5 | 39.8 | 32.1 | 28.2 |
| Private education | 74.3 | 8.1 | 17.6 | 74.4 | 11.8 | 13.8 | 77.9 | 13.0 | 9.1 |

*Source: EU KLEMS and own calculation*

**Table 2: Decomposition in the increase of high skilled workers**

| | Composition effect (1) | Within sector effect (2) | Total increase (3)=(1)+(2) | Weight in total hours (4) | Increase (2)/(4) |
|---|---|---|---|---|---|
| | | | **1980-2005** | | |
| Total industries | 3.48 | 8.68 | 12.16 | | |
| Intensive ICT users | 2.53 | 4.12 | 6.66 | 0.25 | 16.03 |
| Non intensive ICT users | 0.95 | 4.56 | 5.51 | 0.75 | 6.06 |
| | | | **1980-1985** | | |
| Total industries | 1.22 | 0.81 | 2.03 | | |
| Intensive ICT users | 0.64 | 0.38 | 1.02 | 0.21 | 1.83 |
| Non intensive ICT users | 0.58 | 0.43 | 1.01 | 0.79 | 0.54 |
| | | | **1986-1990** | | |
| Total industries | 0.77 | 1.03 | 1.81 | | |
| Intensive ICT users | 0.57 | 0.58 | 1.15 | 0.23 | 2.56 |
| Non intensive ICT users | 0.21 | 0.45 | 0.66 | 0.77 | 0.58 |
| | | | **1991-1995** | | |
| Total industries | 1.13 | 1.49 | 2.63 | | |
| Intensive ICT users | 0.84 | 0.81 | 1.64 | 0.26 | 3.11 |
| Non intensive ICT users | 0.29 | 0.69 | 0.98 | 0.74 | 0.74 |
| | | | **1996-2000** | | |
| Total industries | -0.08 | 2.75 | 2.67 | | |
| Intensive ICT users | 0.14 | 1.40 | 1.54 | 0.27 | 5.14 |
| Non intensive ICT users | -0.23 | 1.35 | 1.13 | 0.73 | 1.86 |
| | | | **2000-2005** | | |
| Total industries | 0.45 | 2.58 | 3.03 | | |
| Intensive ICT users | 0.35 | 0.95 | 1.29 | 0.28 | 3.40 |
| Non intensive ICT users | 0.10 | 1.64 | 1.73 | 0.72 | 2.27 |

*Source: EU KLEMS and own calculations.*

**Table 3: Decomposition in the increase of medium skilled workers**

| | Composition effect (1) | Within sector effect (2) | Total increase (3)=(1)+(2) | Weight in total hours (4) | Increase (2)/(4) |
|---|---|---|---|---|---|
| | | | **1980-2005** | | |
| Total industries | -1.61 | 22.66 | 21.06 | | |
| Intensive ICT users | -1.00 | 8.09 | 7.09 | 0.39 | 20.66 |
| Non intensive ICT users | -0.60 | 14.57 | 13.97 | 0.61 | 23.95 |
| | | | **1980-1985** | | |
| Total industries | -0.18 | 4.02 | 3.84 | | |
| Intensive ICT users | -0.11 | 1.93 | 1.82 | 0.38 | 5.01 |
| Non intensive ICT users | -0.08 | 2.10 | 2.02 | 0.62 | 3.41 |
| | | | **1986-1990** | | |
| Total industries | -0.53 | 6.59 | 6.06 | | |
| Intensive ICT users | -0.61 | 2.62 | 2.01 | 0.38 | 6.91 |
| Non intensive ICT users | 0.08 | 3.97 | 4.05 | 0.62 | 6.39 |
| | | | **1991-1995** | | |
| Total industries | -0.38 | 4.71 | 4.33 | | |
| Intensive ICT users | 0.50 | 1.68 | 2.18 | 0.40 | 4.18 |
| Non intensive ICT users | -0.87 | 3.03 | 2.15 | 0.60 | 0.60 |
| | | | **1996-2000** | | |
| Total industries | -0.45 | 5.64 | 5.19 | | |
| Intensive ICT users | -1.15 | 1.57 | 0.42 | 0.39 | 3.98 |
| Non intensive ICT users | 0.71 | 4.07 | 4.78 | 0.61 | 6.72 |
| | | | **2000-2005** | | |
| Total industries | -0.07 | 1.71 | 1.64 | | |
| Intensive ICT users | 0.38 | 0.30 | 0.67 | 0.39 | 0.76 |
| Non intensive ICT users | -0.44 | 1.41 | 0.97 | 0.61 | 2.32 |

*Source: EU KLEMS and own calculations.*

**Table 4: Estimated parameters**

| | **Column I** | | **Column II** | | **Column III** | |
|---|---|---|---|---|---|---|
| | **All sectors** | | **Intensive users** | | **Non intensive users** | |
| $\beta_{h,m}$ | 0.016 | [1.14] | 0.029 | [1.08] | 0.007 | [0.44] |
| $\beta_{h,\ell}$ | 0.052 | [2.74]*** | 0.009 | [0.28]*** | 0.067 | [2.93]*** |
| $\beta_{h,hard}$ | -0.009 | [3.14]*** | -0.013 | [2.69]** | -0.007 | [2.13]** |
| $\beta_{h,com}$ | -0.008 | [2.74]*** | -0.012 | [2.50]*** | -0.006 | [1.62] |
| $\beta_{h,soft}$ | -0.009 | [3.39]*** | -0.013 | [2.84]*** | -0.007 | [2.22]** |
| $\beta_{h,k}$ | 0.038 | [13.88]*** | 0.032 | [6.78]*** | 0.041 | [12.41]*** |
| $\beta_{m,\ell}$ | -0.002 | [0.11] | -0.038 | [1.08] | 0.021 | [0.97] |
| $\beta_{m,hard}$ | -0.002 | [0.63] | 0.005 | [1.15] | -0.005 | [1.69]* |
| $\beta_{m,com}$ | -0.001 | [0.35] | 0.005 | [1.13] | -0.005 | [1.43] |
| $\beta_{m,soft}$ | -0.001 | [0.50] | 0.006 | [1.27] | -0.006 | [2.05]** |
| $\beta_{m,k}$ | 0.032 | [13.37]*** | 0.029 | [6.11]*** | 0.035 | [12.81]*** |
| $\beta_{\ell,hard}$ | 0.015 | [4.35]*** | 0.015 | [2.79]*** | 0.015 | [3.52]*** |
| $\beta_{\ell,com}$ | 0.013 | [3.70]*** | 0.014 | [2.64]*** | 0.012 | [2.80]*** |
| $\beta_{\ell,hard}$ | 0.014 | [4.33]*** | 0.015 | [2.75]*** | 0.016 | [3.71]*** |
| $\beta_{\ell,k}$ | 0.064 | [19.56]*** | 0.056 | [10.24]*** | 0.068 | [16.90]*** |
| $\beta_{hard,soft}$ | -0.003 | [2.05]** | -0.004 | [1.89]* | -0.002 | [1.17] |
| $\beta_{hard,com}$ | -0.003 | [2.15]** | -0.005 | [1.99]** | -0.002 | [1.19] |
| $\beta_{hard,k}$ | 0.004 | [1.81]* | 0.006 | [1.33] | 0.003 | [1.20] |
| $\beta_{com,soft}$ | -0.003 | [2.02]** | -0.004 | [1.91]* | -0.002 | [1.11] |
| $\beta_{com,k}$ | 0.004 | [1.82]* | 0.006 | [1.34] | 0.003 | [1.20] |
| $\beta_{soft,k}$ | 0.004 | [1.80]* | 0.006 | [1.33] | 0.003 | [1.19] |
| **Obs.** | 575 | | 200 | | 375 | |

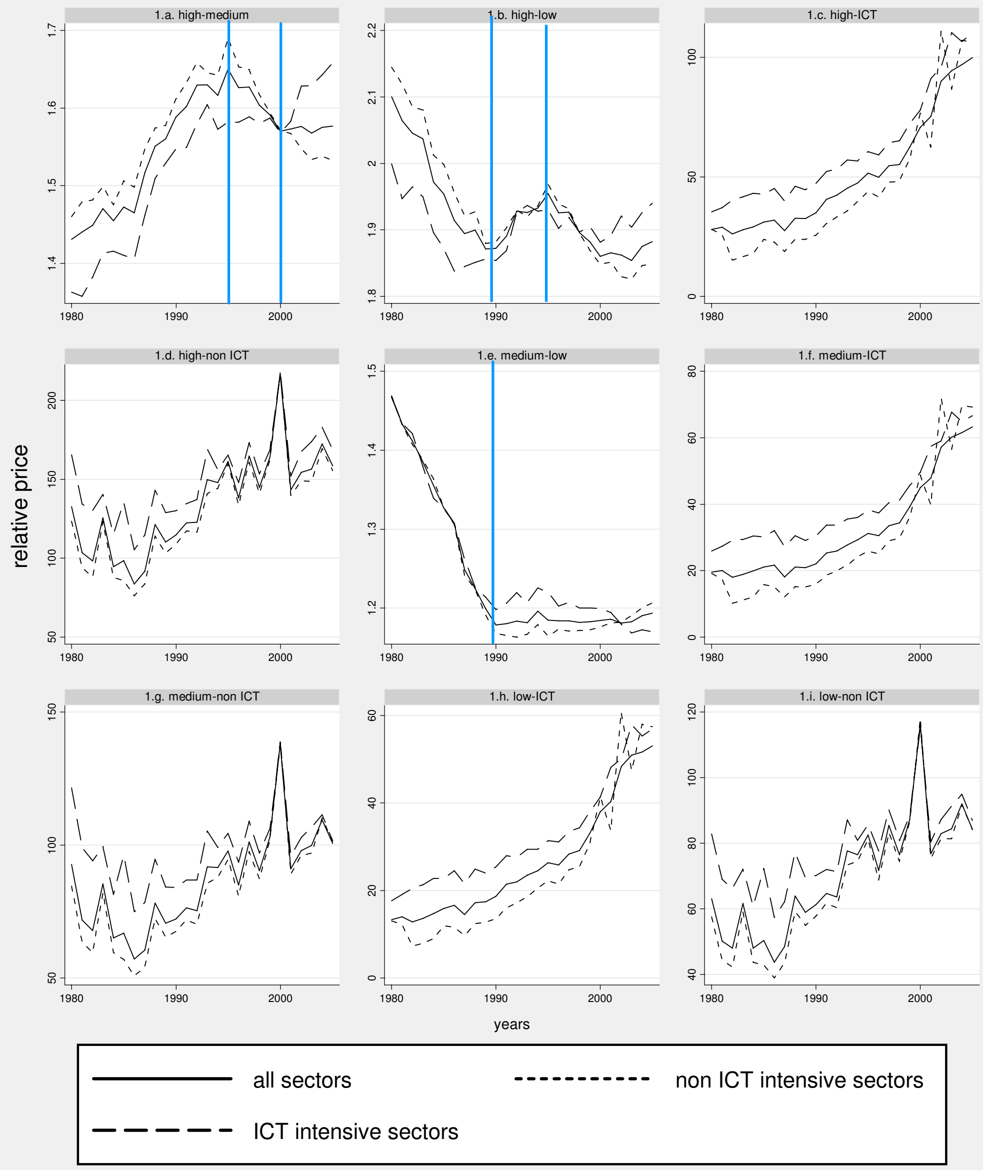
*Figures into brackets ate t−students in absolute terms.*
** significative at 10%; ** significative at 5%; *** significative at 1%.*

Table 5: **Average elasticities of substitution 1980-2005**

| | Column I | | Column II | | Column III | |
|---|---|---|---|---|---|---|
| | **All sectors** | | **Intensive users** | | **Non intensive users** | |
| $ES\,(h,m)$ | 1.56 | [1.16] | 1.64 | [1.07] | 1.34 | [0.47] |
| $ES\,(h,\ell)$ | 1.77 | [2.75]*** | 1.12 | [0.27] | 2.11 | [2.93]*** |
| $ES\,(h,hard)$ | -3.95 | [3.28]*** | -1.96 | [2.76]*** | -7.03 | [2.11]** |
| $ES\,(h,com)$ | -1.53 | [2.89]*** | -0.63 | [2.57]*** | -2.75 | [1.75]* |
| $ES\,(h,soft)$ | -7.85 | [3.34]*** | -3.09 | [2.76]*** | -25.14 | [2.14]** |
| $ES\,(h,k)$ | 1.97 | [13.92]*** | 1.67 | [6.72]*** | 2.24 | [12.40]*** |
| $ES\,(m,\ell)$ | 0.97 | [0.10] | 0.36 | [1.08] | 1.31 | [0.97] |
| $ES\,(m,hard)$ | -0.12 | [0.79] | 2.40 | [1.09] | -4.06 | [1.67]* |
| $ES\,(m,com)$ | 0.68 | [0.38] | 1.83 | [1.09] | -1.76 | [1.56] |
| $ES\,(m,soft)$ | 0.00 | [0.40] | 3.32 | [1.30] | -18.75 | [2.04]** |
| $ES\,(m,k)$ | 1.83 | [13.17]*** | 1.75 | [6.21]*** | 1.93 | [12.92]*** |
| $ES\,(\ell,hard)$ | 4.53 | [4.45]*** | 3.63 | [2.74]*** | 6.21 | [3.53]*** |
| $ES\,(\ell,com)$ | 2.76 | [3.79]*** | 2.46 | [2.57]*** | 3.27 | [2.70]*** |
| $ES\,(\ell,hard)$ | 6.90 | [4.21]*** | 4.64 | [2.72]*** | 19.08 | [3.82]*** |
| $ES\,(\ell,k)$ | 1.70 | [19.52]*** | 1.91 | [10.17]*** | 1.62 | [16.81]*** |
| $ES\,(hard,soft)$ | -14.12 | [2.30]** | -7.60 | [2.13]** | -25.21 | [1.32] |
| $ES\,(hard,com)$ | -46.06 | [2.31]** | -14.98 | [1.69]* | -155.57 | [1.36] |
| $ES\,(hard,k)$ | 2.63 | [1.90]* | 2.60 | [1.36] | 2.90 | [1.38] |
| $ES\,(com,soft)$ | -26.04 | [2.32]** | -8.52 | [1.70]* | -84.26 | [1.33] |
| $ES\,(com,k)$ | 1.94 | [1.90]* | 1.95 | [1.37] | 2.04 | [1.37] |
| $ES\,(soft,k)$ | 3.92 | [1.88]* | 3.21 | [1.35] | 7.19 | [1.36] |
| **Obs.** | 575 | | 200 | | 375 | |

*Figures into brackets ate $t-$students in absolute terms.*
** significative at 10%; ** significative at 5%; *** significative at 1%.*

Figure 1.a Relative prices of factors, 1980-2005




Source: EUKLEMS, Ivie-FBBVA and own estimations

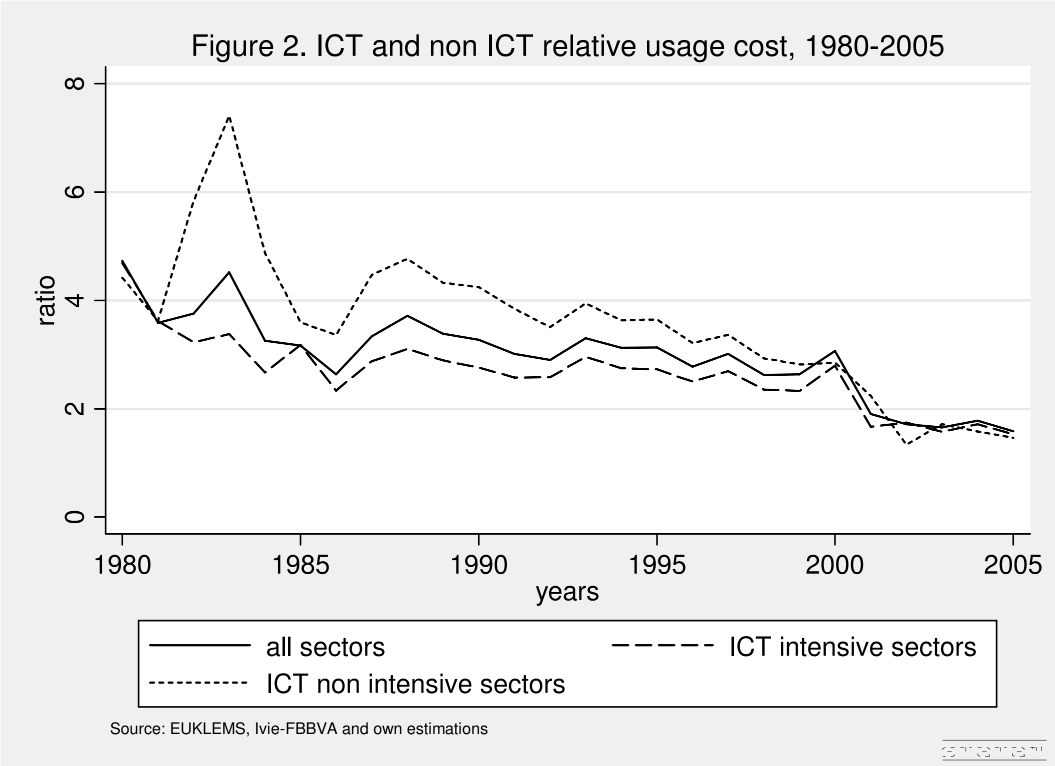
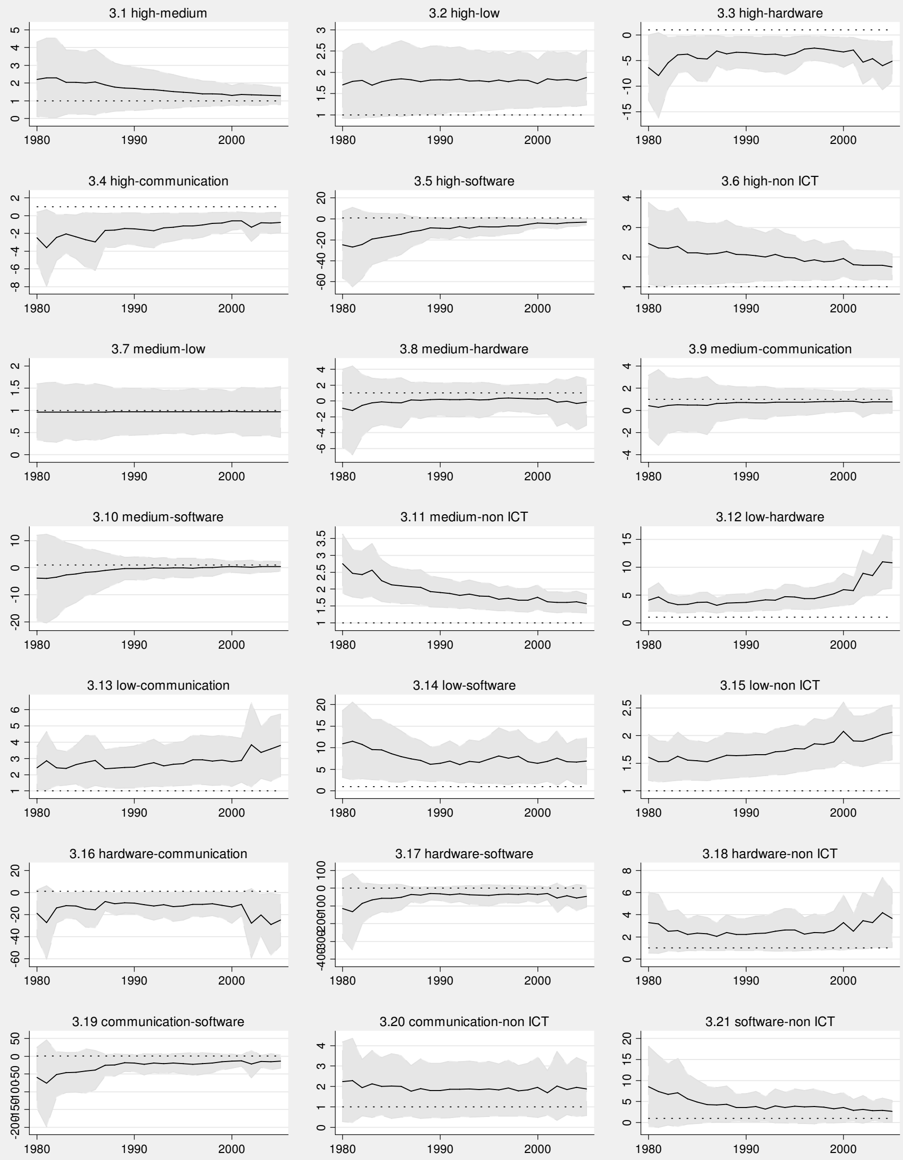


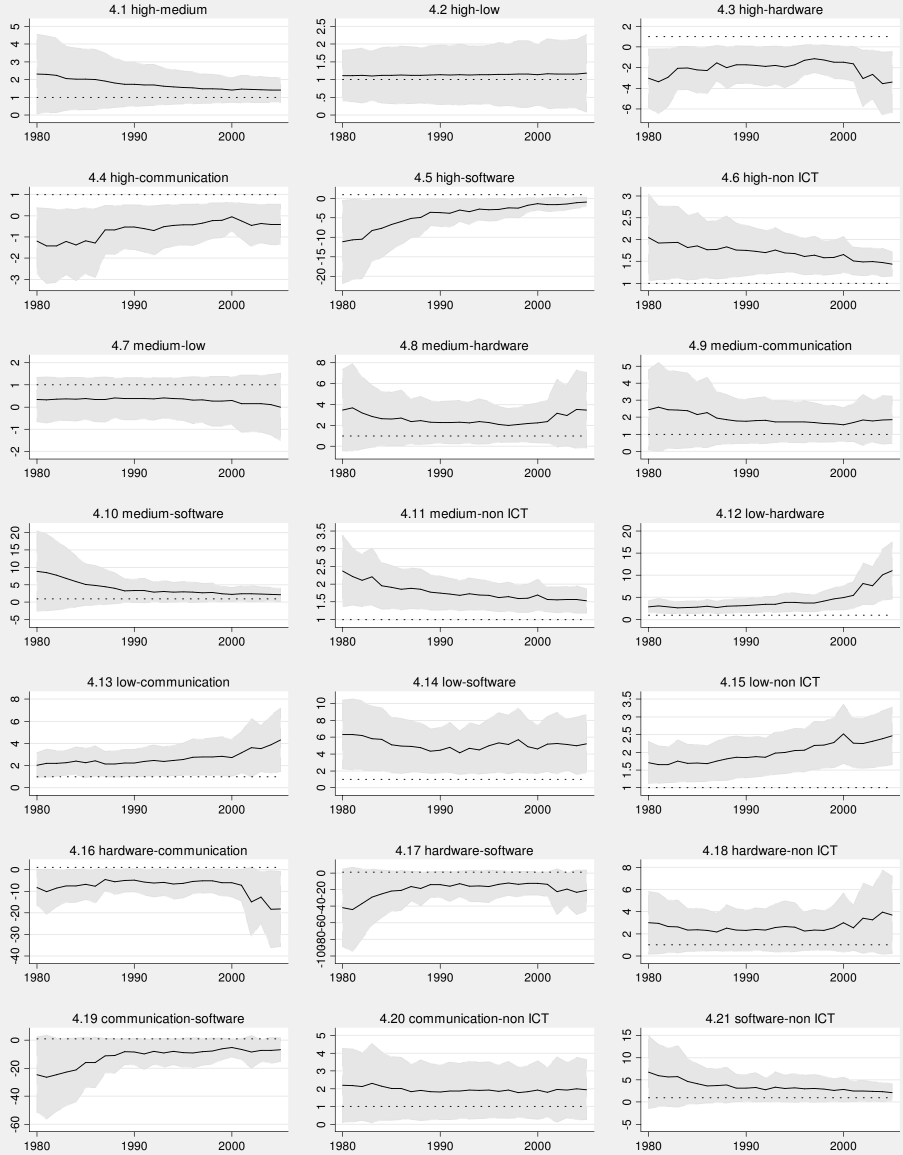
Figure 2. ICT and non ICT relative usage cost, 1980-2005
ratio
0
2
4
6
8
1980
1985
1990
1995
2000
2005
years
all sectors
ICT intensive sectors
ICT non intensive sectors
Source: EUKLEMS, Ivie-FBBVA and own estimations

# Figure 3. Elasticities of substitution, 1980-2005
(all sectors)



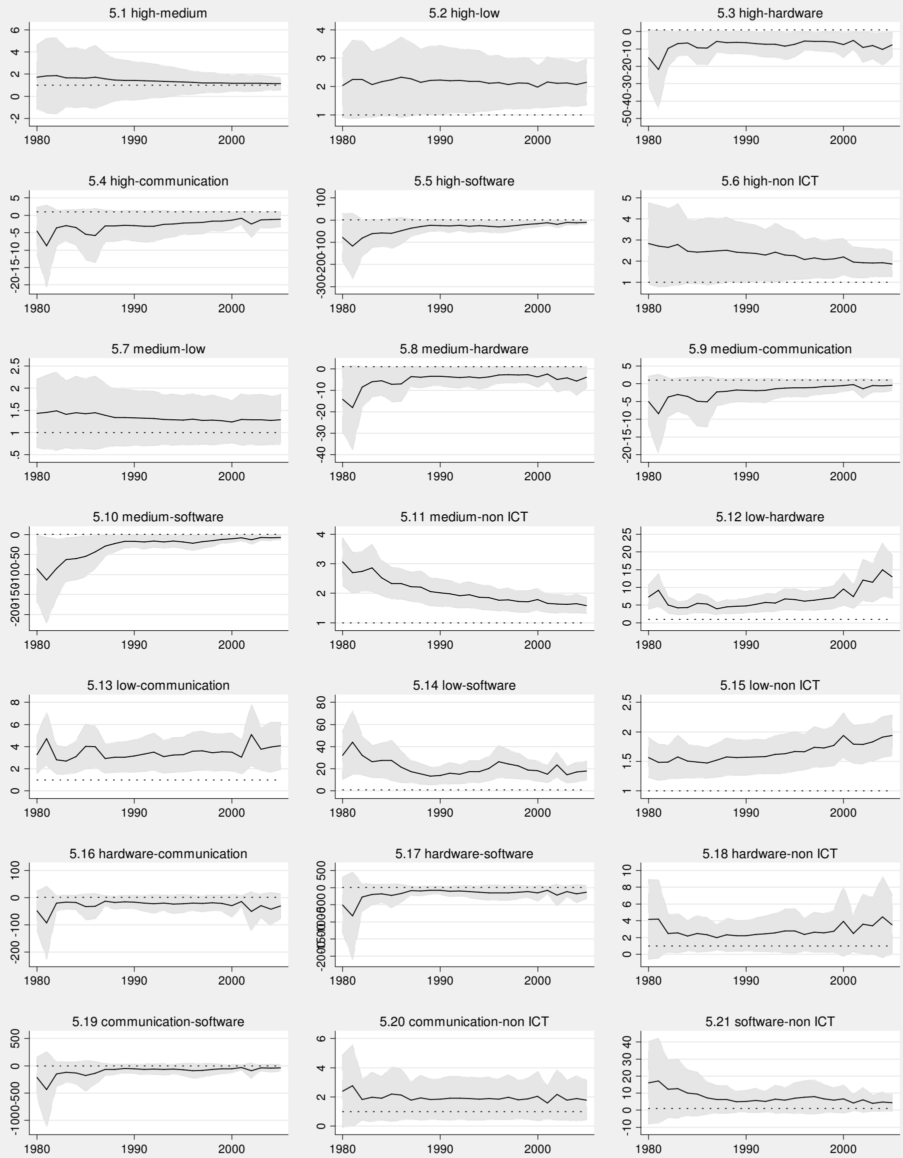

Note: Shadowed areas represent 95% confidence intervals. Dotted lines are fixed to one

# Figure 4. Elasticities of substitution, 1980-2005
## (ICT intensive sectors)




Note: Shadowed areas represent 95% confidence intervals. Dotted lines are fixed to one

# Figure 5. Elasticities of substitution, 1980-2005
## (ICT non intensive sectors)




Note: Shadowed areas represent 95% confidence intervals. Dotted lines are fixed to one

stata™