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# The "New Growth Model". How and with Whom? by <br> Florentino Felgueroso * <br> Sergi Jiménez-Martín** DOCUMENTO DE TRABAJO 2009-39 

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# The "New Growth Model". How and with Whom? ${ }^{\text { }}$ 

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#### Abstract

After the early 90s crisis, Spain had a long period of prosperity that ended abruptly with the recent global crisis. What many did not realized is that Spain, by following a different growth trajectory than a majority of the EU15 countries, was choosing a wrong detour. In this paper, we argue that the growth path chosen in early 90s lead to a wrong accumulation of human capital and technological skills in order to adopt ICT technologies. The adverse demographic structure (the significant decrease in the size of the young cohorts), the dual composition of the population by educational levels (high share of people with low and high educational attainment, and a very low share of medium attainment) and the huge and rapid increase of female participation rates have been key factors in this process. In particular, and in contrast with a majority of the EU15 countries, dropout rates and computer illiteracy have remain high, favoring growth in low skills low productivity sectors and hurting employment opportunities in knowledge intensive sectors. Moreover, the lack of people with medium educational attainment has also been responsible for a growing mismatch of the high-educated population.


The recent crisis has to be viewed as an opportunity to get back to the correct growth track, by reducing incentives to dropout and by favoring skill adjustment. Targeted schooling (to reduce dropout) and training (to increase ICT literacy of medium age and older cohorts) should be priority policies aimed at increasing productivity in the old sectors, creating employment in intensive ICT services sectors and covering the huge gap in professional and technicians in comparison to other EU15 countries. However, some factors that have slowed the adoption of new technologies in the recent past will persist in the coming decade. In particular, the significant decrease of the cohorts of young entrants and the educational path dependencies should continue to act as resilience factors to implement the reforms required to stimulate the change in the growth model. Furthermore, the permanent mismatch of the most abundant university cohorts (those who graduated around the mid-90s), also constitutes a brake on change, given the drastic decline in new graduates in the near future. Thus, policies focused on young second-generation of immigrants and incentives to the entry of skilled immigrants should also be considered.

Keywords: growth model, general purpose technology, ICT, school drop-out, educational mismatch, lifecycle learning, cohort size, employment protection legislation (EPL), female labor force participation.

JEL Codes: J21, J24, J31

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## 1. Introduction

Since the mid'90s until 2007, the Spanish economy experienced a very strong job creation, allowing the employment rate to increase by about 20 percentage points (see Figure 1a). Starting from the last position among the EU15's countries (see Figure 1b), Spain converged to the EU15 average employment rate (15-64 years old), surpassing Italy ( 7 pp ), catching up with France (1pp) and cutting the distance to countries like UK, Germany or Finland (-4-6 pp).


Sources: [a] OECD Labour data base (1960-2007); [b] EPA (Q2, 1977-2009)
Figure 1b: Differences in Employment Rates between
European countries and Spain (population aged 15-64)


[^1]The other side of the coin has been the poor performance of labor productivity and Total Factor Productivity (Figures $2 \mathrm{a} \& \mathrm{2b}$ ). The average of the labor productivity growth was the lowest in the last 40 years and, as a result, stagnated in comparison with the EU15 average. Unlike most EU15 countries, the evolution of Total Factor Productivity has been negative throughout this period.

Figure 2a: Labour productivity \& TFP, in Spain (1970-
2007)


Figure 2b: Productivity per hour worked in EU1 5 countries 2007, EU15 $=100$
$\square$ Gross value added/hour worked, var.1996-2007, 1996=100
$\square$ Gross value added/h our worked, 2007, EU15=100 -TFP (value added based) growth, var.1996-2005, 1996=100


Sources: European Labour Force Survey (Eurostat) \& EU KLEMS database (version March 2007).

Since the second quarter of 2007, the major impact of the crisis on employment has meant a significant step backwards: the employment rate dropped by about 6 pp in two years, returning to levels similar to those of the 60s and 70s and breaking away from most EU15 countries.

There is an almost general consensus that these phenomena have been driven by a growth model too specialized in low-productivity industries such as Construction and Tourism sectors, that are experimenting the major impact of the crisis in terms of employment. Hence, various parties advocate that Spain needs to change its model of growth, from low productivity industries to high productivity ones.

However, empirical evidence shows that this specialization can currently only explain a small part of the gap in labor productivity with other countries. Mas et al. (2008), for example, show that in mid-90s, the industrial composition (specialization effects towards low-productivity industries) explained the major part of differences in labor productivity between Spain \& the EU15, but in the mid-2000s, the situation had reversed: almost $2 / 3$ of the differences were explained by within industry differences. Moreover, the aggregated TFP growth rates continue to be negative (including the ICT sectors, Bentolila et al., 2009), and worst than most EU15 countries.

The evidence also shows that the poor performance of productivity and TFP would be related to the limited relative progress in adopting new technologies, especially ICTs. Since the two main objectives of the so-called "new production model" should be to increase productivity and employment rates, it seems appropriate to analyze why there is such a delay in the use of new technologies in Spain. Although this analysis probably only constitute a part of story, it should help to appraise and understand the origins of the gap between Spain and other the EU countries with higher TFP and employment rates, and discuss the policies required to reduce these gaps.

The ICT is a General Purpose Technology (GPT), which affects all the industries and exhibits skill complementary, that is education and/or training are needed to use them. For this reason, the incentives to adopting new technologies depend largely on the mechanisms operating throughout labor markets: the relative demand and supply of skilled workers, the wage premium, etc.., are factors that have been studied largely, constituting an abundant literature on the interplay between labor market and ICTs. Their adoption has been associated with the increase of relative demand for skilled workers and rising skill premium observed in most countries over the last decades. Furthermore, several studies have shown that the adoption of new technologies is endogenously determined by the relative supply of skilled workers.

In this line, Bentolila et al (2009) have recently given a possible explanation for the poor performance in the adoption of technical advances by the Spanish firms. "They have not managed/found more profitable to exploit the complementarity between new technologies and skilled work". Three reasons can be argued to explain this: (1) the inflow of unskilled labor (immigration) that have made relatively less profitable technological capital, (2) the increase in skill supply has been lower than the raw data suggest and (3) the presence of important barriers to exploiting the technological capital-skill complementarity (product and labor market regulations). As a result, despite the huge increase of high educated workers, there has been a relatively low
demand for skilled labor and a drop in skill premium, in apparent contradiction with other countries, specially the U.S. The proposed solutions necessarily imply the reform of the educational system as well as the labor market, particularly the contracts regulation and the collective bargaining structure.

In this work, we grasp further into these possible explanations and solutions to reverse the situation and accelerate the switch to a new production model in which firms and workers will make a wider use of ICTs. As Bentolila et al. (2009), we focus mainly on the mechanisms operating throughout the labor markets. We argue that the reasons for explaining the low adoption of new technologies in Spain are the combination of ageing, delays in the demand of education and the rapid increase in female labor market participation. These trends are responsible of important cohort size effects (within age group competition for jobs), a limited substitution between groups of workers with different educational levels and ages (EPLs endogenously determined by the educational composition of the population by ages) and the outsourcing of the household production (that boosts the demand for unskilled jobs). The interplay of these effects are causing higher schooling drop-out rates, more educational mismatches and less lifecycle training/learning than in other countries. All of them are indicators of the difficulties of the Spanish economy in adopting new technologies. The trends that are causing them will remain in the medium and long terms, and could be the basis of a more durable recession if drastic reforms are not made in the short term.

The structure of the paper is as follows. In Section 2, we document the process of ICTs adoption in Spain, and compare it with other EU15 countries. Starting from the premise that this adoption depends first on computerization, we analyze the relationship between the use of computers in business and the share of unskilled population for computer use. Section 3 is devoted first to explain, from a theoretical point of view, the effects and barriers to the transition to a production model based on the adoption of a new GPT which exhibits skill complementarities. The aim of Section 4 we assess what kind of investment in human capital is needed to change the production model. In Section 5, we document the recent evolution of school drop-out in Spain. In section 6, we analyze the occupational mismatch among Spanish high educated population. Finally, in Section 7, we summarize the main results of this paper and we discuss policies that would be more effective adopting a new production model based on the knowledge society.

## 2. The adoption of ICTs in Spain

In this section we document the gap between Spain and EU15 countries in ICT use and adoption. In particular we focus in the skills needed for using them, the sectoral differences and the relationship between these variables and the productivity and employment growth.

## ICT capital services

There is an almost general agreement in the recent literature on the ICT spillovers effects at the macroeconomic level. In particular this would explain the gap in TFP between Europe and the U.S., but also that between Spain and other countries in the EU15. Spain has traditionally shared with other countries of southern Europe a lower ratio of ICTs capital services on the total productive capital services. More importantly, during the period 1995-2005, the gap with other EU15 countries has expanded ${ }^{1}$. On the other side, Spain was in the current decade, the EU15 country countries where the ICT capital deepening contribution to labor productivity growth was lower. On the opposite, countries like the U.S., the UK, Finland and Sweden have combined high ICT investment and high non-ICT TFP growth, while countries like Italy and Spain show the opposite (Ark \& Sinclair, 2005).

## The use of ICTs

In any case, several recent studies have emphasized that the difference in the ITC effects on productivity between both sides of the Atlantic depends more on the type of use than on their acquisition. There are still important differences between countries in ICT uses ranging from restructuring the human resources organization, management, research, product innovations to e-commerce, e-learning, e-government etc.

In this sense, some paradoxes arise as shown in Table 1. Spain is the first EU15 country vis à vis to the adoption of broadband by firms in the EU15 countries, but often the last in business use of broadband. Similar paradoxes can be observed using data on ICT adoption by households, Spain also has a very high coverage of broadband but almost of indicators of the Internet use are very low compared with other countries.

## (Table 1 about here)

A somewhat impressionistic way of getting a possible relation between the use ICTs and TFP is to relate the use of computers by workers and the TFP growth rates, but in addition there is also a stronger positive correlation between the first variable and employment rates within the EU-15: the higher is the percentage of workers using

[^2]computers at the workplace, the higher is the TFP growth rate and the higher the employment rate too.


## Skills for the use of computers

The first explanation for the low use of computer related technologies at work is the high fraction of workers without any qualification for using them. Spain, as compared with EU15 countries, has more computer skilled workers but at the same time a high deficit of medium-low skilled workers (workers that can manage computer for working, see Table 2a) and, consequently, a high surplus of computer unskilled workers.


[^3]As it can be observed in Figure 4, there is a strong negative relationship between the percentage of workers that use computers at workplace and the percentage of individuals without skills for using them. Similarly to other Southern European countries, Spain is the country with the highest fraction of unskilled in computer use: $43 \%$ of the population 16-74 can be considered illiterate in relation to computer use, 20 percentage points above Scandinavian countries, Germany and The Netherlands. A large fraction of this gap can be explained by the large differences observed at advanced ages. Only $25 \%$ of the population $55-64$ has some qualification for using computers. Among the younger cohorts the differences are smaller (see Table 2a \& b).

Figure 4: Workers using computers at workplace \& computer unskilled population (2007)

Workers using computers at work (\%)
$\square$ Individuals' level of computer skills: \% unskilled (pop. 16-74)


Source: Information society statistics (2007, Eurostat)

## Use of computers among manual workers

As GPT, the ICT not only can be adopted in a majority of sectors, but also in a majority of occupations, not only those requiring a high level of education. In Figure 6 we show that the relationship between computer use at work is not exclusively observed for ICT-specialized workers but also for manual and non-manual workers. In this sense, Spain is at the bottom in computer use at work for both types of occupations. In this sense it is revealing that the Spanish average use of computers at work for all the occupations is similar to the mean for manual workers in Austria, Sweden, Finland or Denmark.

Undoubtedly, this lack of technology adoption for low-skilled and medium skilled workers should be in the core of any explanation of the poor current performance of the Spanish economy.


Source: Information society statistics (2008, Eurostat)

## Sectors, technologies and ICTs.

One of the key arguments to justify the low productivity path of the Spanish economic (and the subsequent drop in employment) is the specialization in two low productivity sectors: the construction and the tourism sectors. We show in this section that these two sectors, although contribute to the general "trouble" of the Spanish economy, do not explain in full the employment gap of the Spanish economy. In our view, in explaining the (employment) gap between Spain and the EU15 countries it seems more importantly the delay in technology adoption across sectors than the specialization in construction and tourism that is commonly argued.

With the current crisis, is it likely to observe the construction sector coming back to normality, that is, to represent about 4.5 to $5 \%$ of the total employment (see Figure 6 and Table 3). This would imply a fall of about 3.5 to 4 percentage points of the total employment. Likewise, the tourism sector represents about 5 percentage points of the employment rate in Europe and about 8-9 percentage points in Spain. So, also in this case the Spanish average is about 3-4 pp larger. However, in this case the larger contribution is expected to remain at about the same rate.

In order to analyze the differences in sectoral employment composition between Spain and the EU15 countries we use the Eurostat classification which classifies sectors according to their technological intensity (see Table 4).
(Table $3 \& 4$ about here)

Figure 6: Employment rates in Spain and contribution of the Construction Sector


The key differences are not in high-tech sector but in other Knowledge Intensive Services, which make intensive use of ICT but do not generate them. In fact, the countries with higher employment rates are precisely those with a large fraction of employment in these sectors (Scandinavian countries, UK, The Netherlands). In particular, the differences in these sectors explain between 10 and 17 pp of the differences with respect to Spain.

There is a relationship between production of Knowledge intensive services and use of ITC in other services sectors. In the Swedish case, production of ITC services leads to a very high fraction of the population 15-64 working in education, health and social work. In the case of France and Germany, production of ICT leads also to higher fraction of employment in other services but also in medium technology industries.

There seems to be a trade-off between increasing employment in sectors which make higher use of ICT and increasing the use of ICT in existing sectors. Both cases will almost surely increase the level of productivity in Spain. However, while the first strategy will increase the employment rate, the second will make the employment rate more resistant to shocks.

## Adoption of ICTs, productivity \& employment rates.

Since the two main objectives of the so-called "new production model" should be to increase productivity and employment rates, it seems appropriate to analyze why there is such a delay in the use of new technologies in Spain. Although this only is part of the story, it should help to appraise and understand the origins of the gap between Spain and other the EU countries with higher TFP and employment rates, and also to discuss the policies needed to cut these gaps, accelerating the adoption of ICT.

In Table 5 (and Figure 7, panels a to d) we present the correlation coefficients between employment rate, labor productivity, TFP, use of computers at workplace and computer use skills at the EU15 level. We detect a large (positive) correlation between the population using computers at work and all measures of productivity and, especially, employment. It is also relevant the positive (negative) correlation of the percentage of computer medium skilled (\% unskilled computer) population and all the measures of productivity and employment. Thus, it seems well establish the relationship between literacy in the new GPT and productivity and employment rate.
(Table 5 about here)



Sources: Information society statistics \& European Labour Force Survey (2007, Eurostat), EU Klems

## 3. The transition period of the adoption of a GTP

### 3.1 GTP adoption

"Changing the productive model" can be identified with the adoption of a General Purpose Technology (GPT), that is a technology whose introduction affects the entire economic system, being diffused across all sectors and affecting many occupations. Several studies have analyzed the channels through which GPTs affect the economy at the macroeconomic level. Most of them concluded that whilst each new GPT raises output and productivity in the long-run, it can also trigger cyclical fluctuations while the
economy adjusts to it, leading to a productivity slow-down during the transition period. (Helpman \& Trajtenberg, 1994; Brenashan \& Trajtenberg, 1995; Aghion \& Howitt, 1998; Helpman, 1998; Helpman \& Rangel, 1999). For example, the slowdown in productivity growth in US during the 1970s might be related to computerization (David 1991). Furthermore, ICTs are computer based GPTs that exhibit a skill complementarity, increasing the level of schooling required to operate it. This could explain the increases in the relative demand of highly educated workers and the wage inequality/skill premium observed in several countries. (References: Katz \& Krueger, 1997), except in the Spanish case.

The size of the slumps and the timing of slowdowns associated with the arrival of a new GPT depend on several factors, and such recessions can linger for long periods of time (see Helpman, 1998, for a collection of essays on this subject). We focus here on the adjustment channels that operate through labor markets and try to identify them for the case of the Spanish economy. We follow the theoretical approach of HelpmanRangel (1999) who explained the cyclical/productivity adjustment paths by the changes in the educational attainment required by the new GPT and the balance between the gains and loss of experience with new and old technologies.

The distinction between human capital acquired by experience and schooling plays a key role in this approach. The education and training required by the new GPT take place mostly in schools and provide human capital general skills that apply to many technologies. However experience is acquired by working with a specific technology, being then less transferable across technologies than human capital acquired through schooling.

When an inexperienced worker is more productive with the old technology, output declines with the arrival of the new one. However, even when an inexperienced worker is more productive with the new technology, the adjustment can start with a slowdown or a recession. Furthermore, the likelihood of a recession increases the faster productivity rises with experience in the new sector.
Upon arrival of technology-skill complementary GPT, workers compare his expected lifetime income in the old sector with his expected income in the new one. Whenever the latter is larger, young cohorts will decide to extend his/her educational attainment and start afterwards their careers in the new sectors, while older cohorts will invest in training and switch sectors. If older cohorts do not consider profitable switching to the new technology, then the two technologies coexist for a time.

The entry effects on output and productivity refer to those caused by the changes in the sizes of the effective labor force. The first entry effect is due to the fact that younger cohorts have to extend their studies, reducing their labor supply. As a result, the output declines, however the average productivity will increase because they are more inexperienced with the old technology than the older cohorts. This effect is permanent provided that the new cohorts keep expanding their studies. The other entry effect is
caused by workers employed in the old sectors who decide to upgrade their skills via training in order to switch to the new technology. The productivity of these workers will be lower during their training period. It follows that in this case, the adjustment starts with a recession (output and productivity declines) independently of whether inexperienced workers are more productive in the old sector or whether learning is faster in the new one. This effect is only transitory, since once older cohorts who decide to switch have invest in training it disappears.

The "switch effect" refers to experience-driven recessions resulting from the loss of human capital of experienced workers, who switch from old sectors to new ones. If the productivity of labor rises sufficiently rapidly with experience in the new sectors, then even workers who are highly experienced with the old technology switch, even if their initial wage rate is low in the new sector. Every worker who takes a wage cut while switching contributes to a temporary decline in output. Therefore, a recession occurs when many experienced workers switch and the duration of the productivity slow-down will depend on how faster is learning in the new sectors.

Apart of this, expecting a new technology to arrive, individuals stay in school longer in order to prepare to work with it. As a result a negative entry effect precedes the arrival date of the GPT and therefore the recession may start before the technology becomes available. If the arrival of the new GPT is fully anticipated, when it arrives, it is used immediately. But in the case of an uncertain arrival date, the anticipation can lead to educational mismatches. This temporary mismatch is more likely to be converted in a permanent one, the longer the arrival of the new technology is delayed, since the income gains of the switch to the new sectors for the rest of lifetime can be lower than the gains of remaining in the old sectors. As a result, the shift effect will not be compensated by an increase of productivity during the rest of the lifetime and will decrease the productivity at all ages.

In summary, following HR1999, upon arrival of the new GPT, the adoption period and the accompanying slowdown will be more durable and the bust will be more intense depending on shift and switch effects. Shifts effects will be greater the higher the educational level required for the youth cohort, and the gap between the level of education required by the GPT and the one available to older cohorts. The switch effects will be more durable the longer the arrival and the more delayed is the diffusion of the new technologies. In this case, the higher the rate of permanent dislocation and the lower the optimal age to make the switch, which will delay further its adoption.

### 3.2 Implications for the Spanish case

Starting from this reference model, we can discuss other issues not covered by the model and the characteristics of the Spanish economy which could explain their low adoption of ICTs. We are particularly interested in explaining three indicators that can
help explain the delay in adoption of ICT in Spain: the high dropout rate, high educational mismatch, and decreased formation of the elderly.

## (I) Phases of acquiring knowledge and minimum educational level for the use of ICTs

What level of education and training required by new technologies? Is it the same for all generations?

The literature tends to associate the effects of ICTs with more formal education are two types of workers, highly-skilled and low, identifying first with people who have a college attainment. However, if you have to disseminate in the majority of occupations and sectors should also have access to them the less educated. The adoption of a GPT generally passes through several stages characterized by social learning. Probably the first who have had access to ICTs are the workers specifically educated in them, which only constitute a small fraction of the workforce that use it. It must have been an expansion of knowledge, starting probably from the universities (the first use of the GPT) to their students and then transmitted to lower levels of education.

## (II) Diffusion of ICT, firms and sectors

New technologies come in a random way in the HR model, but its introduction and widespread dissemination should be endogenous. Moreover, the theoretical arguments of this approach are essentially based on the role of the supply of skills for the adoption of the GPT, leaving aside the behavior of firms. However, not all sectors use new technologies with the same intensity. Spain has a historic deficit in precisely the sectors that are using ICT intensively. In other countries these sectors had more weight and were more rapidly able to take advantage of the arrival of ICTs. Again, the mass adoption by firms has several phases that depend on social learning among them. The process begins with the leading firms in each sector, which is then transmitted to other firms (Aghion-Howitt, 1998). The greater the number of firms needed for ICTs to be beneficial, the less experience workers will have in these sectors. Moreover, if ICTs are to be combined with experience to be beneficial, new firms will start from a lower initial productivity, precisely because of the lack of experience with ICTs. For example, in education, ICTs do not replace teachers' knowledge or experience, although they can increase them. However, during the learning process, working with ICTs can be less productive than using the blackboard. Thus, the likely productivity loss in the transition period from the old to the new technology may delay or even impede the investment in the new technology.

The likely delay in the adoption could be responsible not only for the overeducation, but also of the schooling drop-out rates, because the size of the sectors that use less the new technologies is important, keeping high both the demand for low skilled workers and the salaries of the starters, thereby reducing the necessity of training between the younger cohorts in order to switch to the new technology.

## (III) Aging and Cohort size effect (within-age group competition)

In HR1999, all cohorts have the same size and level of education after the adoption of new technology, and each person makes his decision based on the expected gain from making the change in the rest of their working lives. There is not, therefore, demographic change, so that all young people make the decision to continue studying. Furthermore, below a certain age, all cohorts make the decision to make the switch, and above this age, do not switch. In this context aging would affect both the entry and switch effects. Aging would affect the entry effect, because it changes the balance between the productivity loss caused by the training of aged cohorts and the likely productivity increase due to reduced labor supply of young cohorts. The switch effect also would be affected by aging because, upon arrival of a new GPT technology, the output and productivity loss will be greater the higher the weight of the older cohorts. When the entry of a new GPT is delayed and the size of the cohort of entrant is large there is an incentive for them to keep studying because the competition for oldtechnology jobs is more intense. Alternatively, when the cohort of entrants is small and the GPT is delayed, many entrants may decide dropping school and taking a job under the old technology.

The cohort size may also influence the likelihood of mismatch. If the fraction of educated individuals grows faster than the demand of jobs for educated people, the likelihood of permanent mismatch is higher the larger cohort size (on the cohort size effects on permanent wages, see the literature initiated by Welch, 1978).

In Figure 8 and Table 6 we show the recent demographic trends for Spain. Figure 8 shows the number of births between 1946 and 2007, and the distribution of the population born in these years in 1991 and January 2008. As it can be observed, the fall in the number of births which began in mid-1970s and ended in the late 90 's has been dramatic, falling by almost half. Moreover, mass immigration since the late nineties has corrected the deficit of native population at virtually all ages, especially for cohorts born after the baby boom. However, immigration alone has not been able to fully compensate the continuous decline of those between 1977 and 1997. Thus, the last period of growth of the Spanish economy has been characterized by a decreasing number of young entrants. This may have strong consequences in the forthcoming decades since the size of youth cohorts will be halved, and so will be the size of the educated entrants.
(IV) Between age group competition \& EPLs

Another possibility not mentioned by HR-1999, is the possibility that new more educated cohorts replace older less educated cohorts who decide not to switch to the new technology. When the benefits of better educated (but still unexperienced) youth are greater than those of seniors with extensive experience in the old but without training in the new technology, cohort substitution may arise. The key mechanism to slow down substitution is the Employment Protection Legislation. Samaniego (2004) shows how the EPL are greater in countries that use less ICTs. However, in the Spanish context, the EPL can be also explained by the higher weight of the older and unskilled population.

In this sense, data on the relative weight of the cohorts in Spain may be related to the high resistance to changes in the system of severance payments in the last 30 years, and also with the high rates of temporary employment observed in Spain. The high prevalence of temporary contracts among the younger cohorts prevents them exploiting the interaction between higher education level, use of new technologies and the specific human capital.

Figure 8: Births and population in 1991 \& 2008 by birth year


Spain is the European country with the largest relative change in cohort size of the population born after the mid-70s. It also shares with other Southern European countries an important education delay, since the highly educated people aged 25-64 represents only $60 \%$ of the less educated (see Table 7). In most EU15 countries, both groups are of about the same size. In the case of Scandinavian countries, the educated double the number of less educated. Apart of this, Spain also shows one of the lower ratios between educated young (25-34 years) and low educated older (35-64 years).
(Table 7 about here)

Again, if higher protection influences adoption delay, companies keep their demand of unskilled jobs. This would help explain why dropout and mismatch rates have not fallen in recent years. On the other hand, under strong EPL, shocks would not be used to dismiss old technology workers, but to dismiss young and temporary workers. These effects may persist for several years as long as the EPL remains basically unaltered and drop-out rates remains high.

## (V) Economic delay and increased female labor participation

A common feature of most countries in recent decades is that higher education has been closely associated with women. In Spain, this relationship has been associated with very low participation and employment rates during the 80s and a spectacular increase since then. This increase was the largest among the EU-15 countries, as can be seen in Figure 9.

Figure 9: Females employment rates in EU15 countries (1960-2007)


The implications of these findings for the basic model are as follows. First, in Spain, it increases the number of educated entrants. This causes a shift effect, since participation at early ages decreases, but life cycle productivity increases, because of a lower probability of leaving the labor market at all ages. Second, the spectacular increase in female participation (full time) which begun in the mid-80s, and that was accelerated in the '90s, caused a considerable shift in the outsourcing of household production.

Finally, the lower mobility of women may also be a factor for the delay in the increase of highly intensive ICT sectors, and may help explain the higher occupational mismatch. First, these sectors are geographically concentrated in a few regions, typically Madrid and Catalonia. On the other hand, the correlation of the level of education within couples may increase the educational imbalance, especially for women (Dolado \& Felgueroso (2007))

## 4. Formal education and other channels to get e-skills

In this section, we document the kind of skills that people require for the use of ICTs, the educational level associated with these skills and the ways to obtain them by age in EU15 countries. Finally, we provide evidence on the relationship between these indicators and the changes in productivity and employment rates.

### 4.1. Education attainment \& computer skills

As we documented in Section 2, adoption and use of ICTs are related to skills people have for using them. In order to assess the educational levels associated with these levels of computer skills, we, first, analyze the correlations between the two types of skills by country; and, second, we use micro data from the same source for the Spanish case.

The correlation coefficients between education and computer skills are shown in Table 8a. The correlation between the proportion of population with low educational level and people who have no qualification for the use of computers is very high. Although decreasing with age, the correlation coefficient for those above 45 is 0.8 , it drops to 0.76 for ages 35 to 44 , and 0.60 for the ages 25 to 34 . It is also important to stress the negative correlation between the weight of the population with secondary education and the computer use proficiency. These data suggest that in order to have high rates of computer use proficiency is more important to have a large fraction of medium educated individuals, than a high fraction of high educated individuals.
(Table 8a and 8b about here)
In Table 8 b we present MNL estimates of the determinants of the level of qualification for computer use ( 3 levels: no skills, medium skills -the reference group, and high
skills) in the population by age group on the basis of a sample from the 2007 Encuesta sobre Equipamiento y Uso de Tecnologías de Información y Comunicación en los Hogares.

We find several interesting results. First, females have, at all ages, lower probability of being either low skilled or high skilled in computer use. So as they specialize in medium skills. Second, the low educated (dropouts) have a much higher (lower) probability of having no skills (high skills) than any other educational group; the opposite is true for high educated. Third, immigrants are likely to have no skills at all ages, especially at the younger ones (the bulk of economic immigrants). Fourth, young employed (16-19, likely dropouts) are very likely not having any skill in computer use. And finally, those employed in the 25-34 age group (which have entered the labor market during the recent boom), are less likely of having high computer skill than employed at other ages.

We present in Table 9 some correlations between education, computer skills, and productivity and employment. Notice, first, that low-educated and computer skilled workers are associated with lower productivity and employment. Alternative, medium educated and skilled are both associated with higher productivity and employment. Finally, the correlation of the employment measures increase with the education and the skill level.

## (Table 9 about here)

How the Spanish case fits in this scenario? As stated before, Spain has a high fraction of high educated and high computer skilled population, but at the same time it has a very high fraction (one of the largest in EU15) of low educated-low computer skilled people, thereby lacking enough people with medium education and medium skilled, which seems to be important for productivity and employment growth. ${ }^{2}$

In Figure 10 we explore more in deep the changes of the education structure of the Spanish population in the recent period of prosperity, 1996-2008. We compare the Spanish structure to that of the EU15 countries. Although the level of education has improved (towards a higher level of education) in these years the comparison is not very favorable to the Spanish case. We highlight three facts: first, the fraction of low educated was among the highest in Europe in 2006 and continues to be there; second, the fraction of medium educated (post-compulsory secondary education before college) was among the lowest and continues there ( 21 points below the average for the EU15, despite an increase of 7 pp in 12 years); third, the fraction of high educated is the only

[^4]one that has evolved very favorable (a 10 pp increase in 12 years), being among the highest in 2008, clearly above EU15 average.

Figure 10: Distribution by education level (EU15, pop. aged 25-64, 1996 \& 2008)


Source: European Labour Force Survey (EULFS, Eurostat)

### 4.2. Channels to obtain e-skills

Another basic question of adoption of new technologies is how people obtain the necessary skills to use them. Do people learn new skills cohorts in schools? How older cohorts are acquiring the skills?

In Figure 11 we present the fraction of individuals receiving ICT training by age group and channel of training. A majority of channels to receiving training are decreasing with age, being courses demanded either by the employer or the employee exceptions which show an inverted U-shaped age profile. However, the fraction of workers receiving IT formation through this channel is, as compared to other EU15 countries, low (see figure 12).

In Table 10 we present probit estimates of the determinants of the probability of acquiring skill through each channels of training using data from the 2007 Encuesta sobre Equipamiento y Uso de Tecnologías de Información y Comunicación en los Hogares.

From these results we extract the following lessons. First, female, with the exception of courses on own initiative, are less likely to use any of the channels. Second, low educated people make less use of any of the channels than more educated individuals; on the contrary, high educated people make more use of the channels than medium educated individuals, being the difference especially relevant in formal education, self-study and learning by doing and Informal Assistance. Third, the probability of taking courses on demand of the employer is greater for non-manual IT workers than for other groups of workers. However, the likelihood of using this channel (0.104) is small as compared to other channels (for example, 0.56 for learning by
doing). In summary, the Spanish case is characterized by a difficult access to e-skill on the part of immigrant and low-education (dropouts) people.
(Table 10 about here)
Figure 11: Channels to obtain IT skills in Spain (\% of individuals by age)


INF. ASSIST: informal assistance from colleagues, relatives and friends and some other ways. FORMAL EDUCATION: formalized educational institution (school, university, etc.) LEARNING BY DOING: self-study (learning by doing)
COURSES-EMPLOYER: training courses and adult education centers, on demand of employer COURSES-OWN: training courses and adult education centers, on own initiative SELF-STUDY: self-study using books, cd-roms, etc.
Source: Encuesta sobre Equipamiento y Uso de Tecnologías de Información y Comunicación en los Hogares (TIC-H, 2007, INE)

In Figure 12 we compare Spain with EU15 countries in terms of main channels to obtain ICT skills. Regarding formal education, only for the 16-25 group Spain is at or above the EU15 average. For the rest of the groups formal education is less prevalent in Spain. Regarding courses demanded or offered by the employer, with the exception of Italy, Spain is well below average, being the gap with northern countries very large. Finally, in terms of courses demanded at own initiative, the gap is less important but it is relevant to note that only for Spain and Italy the fraction that has used this channel is decreasing with age.

Finally in Table 11 we present the correlation between the channels for obtaining e-skills and several measures of productivity and employment. Regarding the formal education channel we find a strong positive correlation at practically all ages with the change in the TFP (especially for those in the group 25-44) and also the employment rate. The strongest positive correlation (0.7) with the employment rate is observed for those above 45. Alternatively, the correlations of this channel with the productivity per hour are negative, especially for workers above 45 . This could be explaining by the HR shift effect which affects the aged workforce. Alternatively, the correlations with the change in productivity per hour are positive at all ages, especially
for those below 45, which have likely benefit from e-skills learning at school. To complement these pieces of information we show at the end of the Table the potential effects on productivity measures from having a lower fraction of dropouts.

Figure 12: Channels to obtain IT skills in the EU (\% of individuals by age)
FORMAL EDUCATION


COURSES ON DEMAND OF EMPLOYER


COURSES ON OWN INICIATIVE


Source: E-skills of individuals, Information Society (2007, Eurostat) (Table 11 about here)

## 5. ¿Why is school drop-out so high in Spain?

In the previous sections, we have shown how ICTs adoption delay can be explained largely by the low educational attainment of its population that determines the equivalent low level of qualification for the use of computers. The share of population with low education (first stage of secondary education or less) among the older population is impressively high vis à vis to other EU15 countries. However, this share can not be explained only by the delay in the demand for education and the lowest level of older cohorts. Since the mid-90s, the weight of low-educated among the younger population has remain very high, partly because of the low educational level of younger immigrants, but mainly because the dropout rates of native youth have declined very little during the period.

Between 1996 and 2008, the reduction of the share of low-educated population at ages 40-59 has been about 20 pp (see figure 13a). However, this difference has decreased substantially among younger age cohorts and, for ages 25-29 the decline was only 9.5 pp . Although in general the differences with other countries in the EU15 have been reduced substantially, for younger population those differences have stalled, maintaining a gap of 20 pp in comparison to other countries of central and northern Europe (see Figure 13b)

This is because in Spain, the dropout rate (defined as a proportion of the population 18 to 24 with low educational level who have left the schooling) which had declined until the mid-'90s, has remained stable since then, over 30\% (see Figure 14). Only Portugal beats Spain in early school leavers. In Italy, starting from levels similar to Spain in the early '90s, this indicator has been halved, being currently 10 pp . below Spain and in Greece drop-out rates are almost 15pp below: half that of Spain!


Source: EPA (INE)

Figure 13b: Dif. in the share of low educated pop. by age (Spain-EU15 countries, pop. aged 20-64, 2008)


Source: European Labour Force Survey (Eurostat)
How has the massive inflow of immigrants affected the share of population with low educational level in Spain? Among the foreign population aged 40-64, the share of low educated is lower than among the native population. However, there are important differences by age: those under 40 have a higher fraction of people with lower educational attainment than natives. To explain why drop-out rates have stagnated, we must bear in mind that the drop-out of foreigners aged 18-24 years are 15-20 points above the natives, and that the share of foreigners of this group of age has increased during the last decade. However, it is not the main explanation as among natives this rate has dropped only 1-2 points in the last decade. (Figure 15a \& 15b).

To evaluate the factors that have influenced these trends in school drop-out rates of native youth and analyze whether they will continue in the short and medium run, we estimate determinants of drop-out rates, using pooled regional data from Spanish Labor Force Survey for the period 1996-2008.

We estimate separated regressions by age and gender for the young native population, considering two age groups: 16-17 and 18-25. The school drop-out is defined here as people with those ages who have a maximum educational attainment equal or lower than compulsory secondary school education and are not classified as students at the time of the survey.

As we have documented in Section 3, we are particularly interested in the effect on early school leaving of several characteristics of the Spanish economy which may have acted and still act as trends:

Figure 14: Early school leavers(*) (Spain \& EU15 countries, pop. aged 18-24, 1992-2008)


Source: European Labour Force Survey (Eurostat)


Figure 15b: Early school leavers(*)


Year
(*) \% of the population aged 18-24 with at most lower secondary education, and not in further education or training. Source: EPA (INE)

The decline of the younger cohort sizes and its possible effect on competition within age group. This size variable is normalized similarly to Welch (1979) and the rest of the literature on the effects of the baby boom and baby bust on the skill premium ${ }^{3}$. The cohort size for population aged 16-17 years in time $t$ includes all persons (including immigrants) in this age group and is computed on the low-educated population aged between 16 and 64 years. That is the ratio between young people and the population with the educational level they would have if they decide to leave school early. For the age group 18 to 25 years, we use the ratio between low-educated population of each age (in two years groups, between 18-25 years old) and population aged 16 to 64 years with this educational level, given that is likely to have left school at $16-17$, taking the opportunity to return to education.

The proportion of low-educated population of older population (ages 26-64) on the total population is introduced to assess the gender educational path dependence and the fact that the regional productive model has a greater reliance on the stock of loweducated population.

The participation rate of middle aged women (26-54 years) is used to evaluate the effects of outsourcing of the household production and the possibility of indirectly affecting the dropout by increasing the demand of low skilled jobs.

Moreover, the fraction of older workers (50-64) would also be a factor in maintaining the old technologies characterizing the regional productive model. This possible effect is evaluated with the mean tenure of low-educated workers with permanent contracts.

We also use other variables such as the regional unemployment rate by gender (which is expected to have a negative effect on the school drop-out rate), the fraction of temporary employment among less educated youths (higher turnover could increase the access to jobs and affect school drop-out), the composition of regional employment by sectors classified according to their technology content, as used throughout this work, and the structure of capital in the region is accounted for by including the capital/output fratio and the ICT capital to capital ratio. Finally, we include regional and time controls.

Tables 12a and 12b present the estimated elasticities of school drop-out rates to these variables. We consider two alternative specifications: one including the sectoral composition of employment in the region and the other including the regional structure

[^5]of capital. Note that the determinants of regional drop-out rates appear to be rather different by gender, and also by age group.

In the case of men just after the compulsory schooling age (16-17 years) our results suggest that a 10 percent increase in cohort size reduces the drop-out rates of young people aged $16-17$ by 6 percent. This implies that a baby bust that reduces the size of the younger cohorts is expected to increase relatively more the drop-out rates. This could be an explanation for the drop-out behavior over the past 15 years (see Table 6), since the arrival of immigrants in this age group has failed to offset the dramatic decline of the native population. Also important, this trend will continue at least another decade.

Middle aged (26-54) female labor force rate has a positive effect on young dropout rates in specification (a). This offers support to our hypothesis on the effects of outsourcing of the household production and the increase in demand of low skill jobs in sectors such as commerce, tourism (less intensive knowledge services and those who have maintained employment of young natives during this period, despite their cohort size has dropped), family helpers, and construction.

Regarding the composition of the sectors, the greater the proportion of low-tech manufacturing, agriculture and construction, the greater the drop-out rate of males aged 16-17. Other variables that may be more cyclical as the regional unemployment rate (by gender) do not seem to affect the dropout rate of this group (at least during this period). Finally, the capital/output ratio decreases dropout rates, while the ICT/capital ratio is not significant for this group.

For women aged 16-17, only unemployment rate in specification (a) and the cohort size (with a similar size than for men) are found significant.

For the population aged 18-25, there would still be the opportunity of returning to school having dropped to $16-17$ years. This is suggested by the fact that the elasticity of the drop-out at this age is less than 1 (about $0.12-0.13$ for females and males). Moreover, for these age groups, the effect of cohort size is positive, for both genders: the larger the weight of the cohort in the population of uneducated, the lower the probability of returning to the formal schooling, provided that he/she has left school early. These results could be interpreted as low educated workers can be good substitutes for old workers in jobs requiring only low education, and for which experience may interact with education as higher educational attainments (Brunello 2007 argue that young workers are poor substitutes of old workers in careers requiring higher education, for example, college education than in careers requiring only high school). For males, we obtain also very high elasticities of school dropouts to the share of low-educated population older age ( $26-64$ ) over the total population in this age group, which indicates significant path dependence and, likely, more employment opportunities in old technology sector. Middle aged female LFPR is significant for males in specification (a). However, we went replace sectoral dummies by capital variables the effect disappears. Sectoral effects are similar than for the younger group.

Finally, capital variables are both significant for both men and women. Higher capital/output ratio reduces dropout rates, and ICT to capital increases it irrespective of gender.

## 6. Occupational mismatch and lifecycle learning

### 6.1 Occupational mismatch among high-educated workers

The increase in population with higher education represents the other side of the coin. The college-educated population under 65 has increased almost sixfold in the last 30 years. Currently is represents $20 \%$ of the population aged 25 to 64 ( $23 \%$ of women and $19 \%$ of men). Compared with 1996, Spain has 2.6 million graduates more, going precisely to overcome this year women and men. Currently, as documented in Section 4, we have already surpassed most of the EU15 countries, and have a proportion of population with higher education similar to that of Scandinavian countries that have considerably higher employment rates.

Despite the spectacular increase in the production of graduates, another important gap which may explain the difference in employment rate with other countries in the EU15, is the low weight of non-manual occupations, especially the high skilled jobs, technicians and other professionals.

Figure 16a shows that the difference in employment rates by countries is essentially due to differences in the percentage non-manual workers. There is a clear positive relationship between employment rates and the weight of these jobs in the working age population, while (excluding Portugal), there are no significant differences between employment rates and proportion of white collar workers. Furthermore, Figure 16b also shows that the difference in employment rates in Spain with countries like Finland, Sweden, Holland, Denmark, UK and Germany can be explained almost in a ratio of 1 to 1 by the gap in technical and professional jobs. In addition to this evidence, Table 13 presents the number of white-collar jobs, and among these, technicians and professionals that should be created in Spain to have a rate of employment and occupational structure similar to that of the rest of the European countries in the first quarter of 2009.
As it can be easily seen, to achieve European Standards, Spain should increase significantly non-manual (excluding tourism) jobs and reduce the manuals ones. To put this in numbers, in order to have an employment rate similar to The Netherlands, Denmark or Sweden, Spain has to increase the number of job between 20 and $27 \%$, decreasing manual jobs between 16 and $24 \%$ and increasing non-manual between 47 and $60 \%$ (especially technicians and professional jobs that should increase between 63 and $86 \%$ ). Note that, with the exception of Austria, Spain would need to reduce manual jobs, and increase the non-manual ones when comparing with any of the EU15.

Figure 16a: Manual \& Non-manual occupations vs Employment rates (EU15 countries, 2009Q1, population aged 15-64 years)


How to explain this gap in technical and professional jobs if we catch up most of the EU15 countries in supply of educated workers? The explanation goes through the mismatch or misalignment of the educational level with occupations. Again, the gap in this particular indicator helps explain the employment difference with other EU15 countries, because the higher the occupational adjustment of the high educated individuals the higher the employment rate is (especially for women).
Table 14 shows the pre-crisis proportion of population with tertiary education adjusted, not adjusted, unused. Spain is the last country in the EU15 in this ranking: the last country in terms of high educated people working in non-manual jobs, and also the last in terms of high educated working as a managers, professionals and technicians. (only $53.9 \%$ versus an EU15 average of $65.9 \%$ ).

In Figure 17 we show how the EU15 countries with higher adjustment of their graduates, are also those with higher employment rates, especially for women.
Turning back to the case of Spain (see figure 18) we observe that along the increase in the employment of graduates (from 65 in 2006 to $75 \%$ in 2007) the mismatch ${ }^{4}$ has also increased in the 1996-2007 period (from 21 to $34 \%$ ). Note that the fraction of well match has remained practically stable at $43-44 \%$. This reveals that many of the jobs

[^6]created for graduates have been of poor quality. Note that during the crisis, the employment rate of graduates has been falling so has done the fraction of graduates mismatched.

Figure 16b: non manual workers by skills vs. employment rates [Dif. (EU15 countries - Spain), 2009Q1, population aged 15-64 years]


Managers, technicians \& professionals: ISCO 1-3; Other non-manual occupations: ISCO 4-5; Source: European Labour Force Survey (EULFS, Eurostat)
(Table 13 and 14 about here)
Figure 17: Share of well-matched high-educated pop. vs employment rates (total population) (EU15 countries. 2007. \%/pod. 15-64)


Source: European Labour Force Survey (EULFS, Eurostat)
Tables 15 a and 15 b shows that although the proportion of adjusted diploma and university graduates has remain stable at $43-44 \%$, its composition by level of education, gender and age has changed substantially. The increase in the fraction of unadjusted individuals has been observed at all ages (especially below 39), gender and educational
level. Apart of this, gender differences generally result in a better alignment for all ages for males in the case of graduates, and for women in the case of the Diplomas.

In Figure 19a and 19d we evaluate whether the educational mismatch is temporary or permanent. That is, do people adjust along their career? From figure 19a this seems to be the case as the number of mismatched university graduates is negatively related to tenure. However in 2009-II, more than $1,000,000$ of mismatched workers and 500,000 of non-employed got their graduation at least 11 years ago ( $27 \%$ of university graduates below age 64), which gives an idea of mismatch persistence. In figure 19b we show the persistent different in the fraction of temporary contract of adjusted and unadjusted diploma and university graduates.

Figure 18: Occupational adjustment of skilled workers (\% graduates < 65)


Source: EPA (INE)


Figure 19b: Temporary employment rates of univ. graduates 1996-2009 (Q2)
$\longrightarrow$ Mismatched $\simeq$ Well-matched


Source: EPA (INE)

## Skill premium and mismatch

Along with the increase in the fraction of population well educated, the increase in the fraction of diploma and graduates unadjusted can help explain the decreasing skill premium.

In Table 16 we present the estimated skill premium by education level using data from the Encuesta de Estructura Salarial in 1995, 2002, and 2006. The regressions include a standard set of demographic controls. First of all, the premium has been reduced for all the educational groups above primary. In the case of educational levels associated with non-manual jobs, the decrease has been more pronounced (about 17 pp between 1995 and 2006). It is important to note that premium reduction have been considerable larger for unadjusted diploma and graduated than for the adjusted ones. At the end of the day, the premium for adjusted diploma and graduates nearly doubles that of unadjusted. Thus, the fall of the skill premium is not only due to falling premium for diploma and graduates but also because of the increase in the fraction of them that are unadjusted (Crowding-out effect, see Dolado et al., 2000).

In Table 17 we present some estimates of the probability of being well-matched and skill premium for diploma and university graduates using individual data from the Encuesta de Estructura Salarial. In addition of the set of controls used in Table 16 we control for within firm workforce composition.

It is revealing to observe that the greater is the weight of low educated individuals in the firm the greater is the probability of being mismatched. More importantly, this effect is of increasing importance. The fraction of low educated in the firm also has effect on wages, by reducing them. The fraction of older workers (50+) has the opposite effect since it increase the probability of being adjusted and increases (not surprisingly) wages. Finally, the fraction of individuals with a permanent reduced
at the beginning of the period the adjustment probability, but its effect has dissipated along the period.

In Table 18 we present some estimates of the adjustment of qualifications to occupations for diploma and university graduates aged 22-35 by gender. Again we present two specifications: one including the sectoral structure of employment and the other replacing these factors by capital structure variables.

We have found a number of interesting results. First, cohort size, the unemployment rate and the fraction of public administration employment decrease the probability of being adjusted for both genders. Note that the share of medium educated individuals reduces the probability of having a good match for women. It is also important to note, that the share of low and medium tech manufactures reduce the adjustment probability for women. Finally, capital to output ratio increases the adjustment probability and the ICT capital ratio reduces it for both genders.

### 6.2 Learning

To conclude this section we present in Table 19 some preliminary estimates of the determinants of the probability of receiving some training (in the last month) for prime age (36-49) cohorts. We use $2^{\text {nd }}$ quarter data from the Spanish labor force survey in the 1996-2008. Cells are defined by combination of region, age (two years), gender and region. Again we present two specifications one including the sectoral structure of employment and the other replacing them by capital structure variables. For both gender the share of low educated workers decreases (with an elasticity of about 0.75) the probability of receiving training and the fraction of older workers increases it (with an elasticity of about 0.35 and 0.7 , depending on the specification and gender). The more weight the construction or the public administration sectors have, the less training is observed in these age groups. For example, each percentage point increase of the share of the construction sector decreases the training probability by 0.20 .

## 7. Conclusions

After a long period of prosperity, and in barely two years, the Spanish employment rate has fallen to the level it had in the seventies, similar to the current Greece level. The stagnant labor productivity growth and the negative trend of total factor productivity during the last decade and a half have been the other side of the coin. Empirical evidence shows that these phenomena are due not only to a production model that specializes in low-productivity sectors, such as construction and tourism, but also to a lower level of productivity in practically all sectors.

The delay in ITC technology adoption is one of the key factors in explaining the productivity and the employment gaps with respect to EU15 average. Those EU15
countries that have delayed less the adoption of these technologies are the ones for which TFP has grown more in recent decades and also those with higher employment rates. It seems reasonable to argue that if the change of the production model should be aimed to close the gaps of the Spanish economy in terms of productivity and employment rates, it should focus on the widespread adoption of ICTs. Therefore, in this paper we have analyzed How and with Whom this technology adoption process can be carried out. Also important, we have to ask what are and what will be the effects of the transition process between the old and the new production model in terms of productivity and employment, and what kinds of barriers the process is facing.

Individual investments in the education and training required by the adoption of ICTs depends crucially on labor market incentives, in particular, the expected wage/productivity gains obtained by changing from old to new technologies. In this context, the age distribution of the population is also an important factor, in the sense that older workers are more opposed to technological change. Apart of this, investment in training of new technologies will also depend on the balance between the loss of productivity achieved under the old, as well as the productivity path under the new technologies. Notice that this balance depends on experience and the level of education, being the balance more positive for the educated than for the less educated.

During the adoption period of new technologies negative effects on aggregate variables such the growth in average productivity and employment rates can be observed. These negative effects can lead to a more or less severe recession and a slowdown economic rather long, depending on the speed at which educational investments are made, and the productivity balance between the old and the new technology. In this sense, the greater the proportion of the population that does not want to change to the new technology, the greater the demand of job protection they will have.

Finally, the greater the delay in the widespread adoption of new technologies, the lower the utilization of human capital investment and the longer the period of economic slowdown (associated to lower productivity rates, educational/skill premium). It also implies less incentive to reduce dropout rates, greater probability that the educational of high-educated workers will become permanent, and less training throughout working life.

In this work we have shown evidence for all these facts in Spain. These pieces of evidences help explain the delay in widespread adoption of ITCs:
(i) The highest school dropout rate amongst EU15 countries (jointly with Portugal). It can not be explained by a possible composition effect due to the massive inflow of immigrants to Spain: the dropout rate of native population has only decreased by 1-2 pp since the mid-90s, after a period of continuous decline.
(ii) The highest (in Europe) rate of occupational mismatch of population with high educational attainment throughout the EU15. It has also remained stable since the mid-

90 s, so that the employment rate of this group has increased at the expense of mismatch, phenomenon which, in turn, explains most of the decline of the educational premium.
(iii) One of the lowest rates of learning throughout working life, especially vis à vis to training of employees and the unemployed, despite having one of the populations with lower educational attainment among older people.

We argue that the key differences between Spain and other EU countries in the adoption of new technologies are related to the fact that their arrival has coincided with at least three very unfavorable characteristics of the Spanish population: its ageing (specifically, the huge decrease of youth population), the accumulated delays in the demand of education and in the female labor force participation. These facts have had strong consequences on the size of entrants cohorts, the demand of education (because of increasing working opportunities), on the occupational adjustment of diplomas and college graduates, and, consequently, on the wage premium. The educational path dependences (the high share of primary and the low share of medium educated people) have also been important factors for explaining dropout and occupational mismatch. In particular, a very important share of the highly educated has been employed in jobs requiring only medium-skills for the use of computers due to the lack of people having a medium educational attainment. The rapid increase of female labor force participation in the last decade has also increased the demand of low skilled services (externalization of home production), and has favored, given the scarcity of native population, immigration. More importantly, it has also increased the incentives to dropout for native youth population. We believe these factors could also explain one of the findings of this work: whereas higher capital/output ratios help reduce school drop-out and increase the rate of well-matched workers, higher contribution of ICTs to the capital services increases dropout rates and lowers matching and training rates, which goes against the change of production model.

The recent crisis has to be viewed as an opportunity to get back to the correct growth track, by reducing incentives to dropout and by favoring skill adjustment. Targeted schooling (to reduce dropout) and training (to increase ICT literacy of medium age and older cohorts) should be priority policies aimed at increase productivity in the old sectors, create employment in intensive ICT services sectors and cover, as compared to other EU15 countries, the huge gap in professional and technicians.

However, the transition period is not going to be an easy one since some of the factors that have slowed the adoption of new technologies in the recent past will persist in the coming decade. In particular, the significant decrease of the cohorts of young entrants and the educational path dependencies should continue to act as resilience factors to implement the reforms required to stimulate the change in the growth model. Furthermore, the permanent mismatch of the most abundant university cohorts, those graduated around the mid-90s, also constitutes a brake on change, given the drastic decline in new graduates in the near future. Thus, policies focused on young second-
generation of immigrants and incentives for newly skilled immigrants should also be considered.

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## Appendix: Tables

Table 1: Adoption of ICT by businesses in EU15 countries (2008)

|  | BROA |  | AEBUY |  | AESELL |  | INV |  | LANEX |  | OSOPEN |  | SECPRO |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| ES | 92 | DE |  | DE |  | DK | 43 | LU | 61 | DE | 20 | DE |  |
| FI | 92 | SE | 68 | IT |  | BE | 36 | SE | 48 | AT | 16 | NL | 10 |
| FR | 92 | DK | 62 | UK | 35 | IT | 29 | FI | 46 | FI | 16 | SE | 10 |
| BE | 91 | UK | 56 | NL | 32 | NL | 29 | DK | 45 | LU | 16 | DK | 9 |
| SE | 89 | IE | 55 | DK | 25 | DE | 27 | FR | 45 | BE | 15 | IE | 9 |
| LU | 87 | AT | 45 | IE | 25 | FI | 25 | BE | 44 | FR | 14 | UK | 8 |
| UK | 87 | NL | 45 | EU15 | 20 | LU | 24 | IE | 41 | NL | 14 | AT | 7 |
| EU15 | 86 | BE | 42 | SE | 20 | PT | 24 | DE | 38 | EU15 | 13 | BE | 6 |
| NL | 86 | EU15 | 42 | PT | 19 | EU15 | 22 | NL | 35 | IT | 13 | EU15 | 6 |
| DE | 84 | FI | 42 | BE | 18 | IE | 21 | AT | 34 | IE | 11 | PT | 6 |
| IE | 83 | LU | 34 | AT | 17 | FR | 20 | EU15 | 33 | SE | 10 | FI | 5 |
| IT | 81 | PT | 29 | FI | 16 | AT | 17 | UK | 29 | DK | 9 | FR | 5 |
| PT | 81 | IT | 28 | FR | 14 | SE | 17 | IT | 25 | PT | 9 | ES | 3 |
| DK | 80 | FR | 25 | ES | 11 | ES | 12 | PT | 25 | ES | 8 | LU | 3 |
| AT | 76 | ES | 21 | LU | 11 | UK | 11 | ES | 19 | UK | 8 | IT | 2 |

BROAD: Enterprises with broadband access; AEBUY: Enterprises having purchased via computer mediated networks; AESELL: Enterprises having received orders via computer mediated networks; INV: Enterprises sending and/or receiving e-invoices; LANEX: Enterprises using LAN and Intranet or extranet in reference year; OSOPEN: Enterprises using open source operating systems; E_SECPRO: Enterprises selling on the internet and offering the capability of secure transactions.
All sectors, except financial sector ( 10 employed persons or more)
Source: Information society statistics (2008, Eurostat)
Table 2a: Gaps between Spain \& EU15 countries in individuals'computer use skills (\% of population 16-74 years 2007)

|  | Unskilled | Low-medium | High |
| :--- | :---: | :---: | :---: |
| DK | 22 | -14 | -8 |
| NL | 22 | -18 | -4 |
| SE | 21 | -22 | 1 |
| DE | 18 | -18 | 0 |
| FI | 15 | -14 | -1 |
| AT | 14 | -9 | -5 |
| UK | 14 | -16 | 2 |
| FR | 9 | -10 | 1 |
| EU15 | 8 | -10 | 2 |
| BE | 5 | -11 | 6 |
| ES | 0 | 0 | 0 |
| IE | -3 | -7 | 10 |
| PT | -10 | 4 | 6 |
| IT | -13 | 4 | 9 |
| GR | -15 | 2 | 13 |

Table 2b: Gaps between Spain \& EU15 countries in individuals'computer use skills by age (\% of computer unskilled, 2007).

|  | $\mathbf{1 6 - 7 4}$ | $\mathbf{1 6 - 2 4}$ | $\mathbf{2 5 - 3 4}$ | $\mathbf{3 5 - 4 4}$ | $\mathbf{4 5 - 5 4}$ | $\mathbf{5 5 - 6 4}$ | $\mathbf{6 5 - 7 4}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| DK | $\mathbf{2 2}$ | 6 | $\mathbf{1 2}$ | 23 | 31 | 42 | 32 |
| NL | 22 | 8 | 14 | 25 | 34 | 38 | 26 |
| SE | 21 | 5 | 10 | 21 | 26 | 41 | 32 |
| DE | 18 | 6 | 13 | 22 | 27 | 37 | 24 |
| FI | 15 | 7 | 14 | 23 | 23 | 28 | 12 |
| AT | 14 | 2 | 9 | 17 | 24 | 27 | 19 |
| UK | 14 | 0 | 5 | 10 | 23 | 32 | 15 |
| FR | 9 | 5 | 10 | 11 | 12 | 19 | 4 |
| EU15 | 8 | 1 | 2 | 8 | 13 | 21 | 12 |
| BE | 5 | -4 | -2 | 8 | 11 | 18 | 9 |
| IE | -3 | -22 | -10 | -5 | -2 | 2 | 4 |
| PT | -10 | 1 | -9 | -14 | -18 | -1 | -3 |
| IT | -13 | -15 | -17 | -10 | -8 | -1 | -4 |
| GR | -15 | -7 | -13 | -14 | -17 | -11 | -5 |

Source: Information society statistics \& European Labour Force Survey (2007, Eurostat)

Table 3: Employment in the construction sector /Pop 15-64

|  | $\mathbf{1 9 9 6}$ |  | $\underline{\mathbf{2 0 0 7}}$ | $\underline{\mathbf{2 0 0 9}(\mathbf{Q 1 )}}$ |
| :--- | :---: | :---: | :---: | :---: |
| Ireland | 4.3 |  | 9.3 | 5.6 |
| Spain | 4.5 |  | 8.7 | 6.3 |
| Portugal | 5.3 |  | 7.9 | 7.1 |
| Austria | 5.3 |  | 5.9 | 5.9 |
| UK | 4.8 | 5.9 | 6.0 |  |
| Greece | 3.7 | 5.4 | 5.1 |  |
| Luxemburg | 5.4 | 5.4 | 5.0 |  |
| Denmark | 4.9 | 5.4 | 4.9 |  |
| Italy | 3.9 | 5.0 | 4.9 |  |
| Finland | 3.0 | 4.9 | 4.8 |  |
| Sweden | 3.9 | 4.7 | 4.6 |  |
| Germany | 6.3 | 4.6 | 4.7 |  |
| Netherland | 3.8 | 4.5 | 4.6 |  |
| France | 4.1 | 4.4 | 4.7 |  |
| Belgium | 3.8 | 4.3 | 4.5 |  |
| EU15 | 4.7 | 5.5 | 5.2 |  |
| EU15 - SP,PT,IE | 4.8 | 4.9 | 5.0 |  |

Sources: European Labour Force Survey (Eurostat)

Table 4: Distribution of employment/pop by sectors
(Dif. EU countries - Spain, 2007, \% pop 15-64)

| Country | MANUFACTURING |  |  | SERVICES |  |  |  | Construction Agriculture$\&$ fishing |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | High | Medium | Low | Knowledge intensive (HTEC) | Other <br> Knowledge intensive | Public Admin. | Other services |  |  |
| SE | 0.4 | 1.2 | -0.9 | 1.9 | 15.7 | 0.2 | -4.2 | -0.8 | 2.1 |
| DK | 0.6 | 1.1 | 0.3 | 1.3 | 14.2 | 0.5 | -2.0 | -3.4 | -0.8 |
| NL | 0.2 | -1.3 | 0.5 | 1.3 | 12.6 | 1.0 | -3.1 | -4.2 | -0.8 |
| UK | 0.4 | -0.1 | -1.3 | 1.1 | 10.7 | 0.9 | -2.6 | -4.0 | -1.5 |
| FI | 1.2 | 1.1 | 0.4 | 1.3 | 9.1 | -0.7 | -4.2 | -3.8 | 0.1 |
| IE | 1.5 | -1.8 | -1.0 | 0.6 | 5.5 | -0.6 | -2.6 | 0.5 | 0.4 |
| DE | 0.9 | 4.7 | 0.1 | 0.5 | 5.4 | 1.2 | -3.3 | -4.1 | -1.4 |
| FR | 0.6 | 0.4 | -0.9 | 0.3 | 5.0 | 2.6 | -4.3 | -4.3 | -0.8 |
| BE | 0.2 | 0.6 | -0.7 | 0.5 | 4.8 | 2.5 | -5.6 | -4.4 | -1.8 |
| AT | 0.7 | 2.2 | 0.1 | -0.1 | 3.2 | 1.0 | 0.7 | -2.8 | 0.7 |
| IT | 0.5 | 1.7 | 0.1 | -0.1 | -0.3 | -0.4 | -3.8 | -3.8 | -0.7 |
| PT | 0.0 | -0.4 | $3 \cdot 5$ | -0.7 | -1.2 | 0.5 | -0.7 | -4.8 | 5.1 |
| GR | -0.1 | -2.4 | 0.1 | -0.7 | -2.2 | 1.3 | -0.9 | -3.3 | $3 \cdot 7$ |

Sources: European Labour Force Survey (Eurostat)
Table 5: Correlations coefficients between employment rate, labor productivity, TFP, use of computers at workplace \& computer use skills (EU15 countries, 2007)

|  | Productivity <br> per worker <br> $\mathbf{2 0 0 7}$ | Productivity <br> per hour <br> $\mathbf{2 0 0 7}$ | Var. <br> TFP <br> $\mathbf{1 9 9 5}$ | Employment <br> rate | FT Eq. <br> emp. Rate |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| (EU15=100) | (EU15=100) |  |  |  |  |
| 2007 |  |  |  |  |  |

Note: date for computer users and skills in 2007, except for TFP (2005).
Sources: Information society statistics \& European Labour Force Survey (2007, Eurostat), EU Klems

Table 6: Population growth by age group (Spain, 1971-2023, 2007)

|  | 1971 | 1981 | 1991 | 2001 | 2008 | 2013 | 2018 | 2023 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathbf{1 5 - 1 9}$ | 100 | 121 | 124 | 95 | 85 | 78 | 81 | 88 |
| $20-24$ | 100 | 115 | 128 | 126 | 110 | 90 | 82 | 85 |
| $25-29$ | 100 | 112 | 136 | 150 | 160 | 122 | 100 | 91 |
| $30-34$ | 100 | 118 | 135 | 159 | 193 | 174 | 133 | 109 |
| $35-39$ | 100 | 94 | 105 | 135 | 160 | 169 | 153 | 117 |

Sources: EPA \& Census (INE)

Table 7: Relative cohort size by educational attainment (EU Countries, 2008)

|  | High 25-64/ <br> Low 25-64 |  | High 25-34/ <br> Low 35-64 |
| :---: | :---: | :---: | :---: |
| PT | $\mathbf{0 . 2 0}$ | PT | 0.11 |
| IT | $\mathbf{0 . 3 1}$ | IT | 0.12 |
| GR | $\mathbf{0 . 5 8}$ | GR | 0.23 |
| ES | $\mathbf{0 . 6 0}$ | AT | 0.28 |
| EU15 | $\mathbf{0 . 8 2}$ | ES | 0.29 |
| FR | $\mathbf{0 . 9 1}$ | EU15 | 0.30 |
| AT | $\mathbf{0 . 9 5}$ | FR | 0.38 |
| BE | $\mathbf{1 . 0 6}$ | BE | 0.38 |
| IE | $\mathbf{1 . 1 1}$ | NL | 0.38 |
| NL | $\mathbf{1 . 2 0}$ | UK | 0.42 |
| UK | $\mathbf{1 . 2 1}$ | DE | 0.44 |
| DK | $\mathbf{1 . 5 4}$ | DK | 0.51 |
| DE | $\mathbf{1 . 7 3}$ | FI | 0.53 |
| FI | $\mathbf{1 . 9 3}$ | IE | 0.56 |
| SE | $\mathbf{2 . 1 4}$ | SE | 0.74 |

Table 8a: correlation coefficients between education \& computer skills, by age (EU15 countries, 2007)

|  | Age 25-34 | Distribution of pop. by educational level (\%) |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | Low | Medium | High |
|  |  |  |  |  |
|  | Unskilled | 0.606 | -0.375 | -0.320 |
|  | Low-medium | -0.691 | 0.357 | 0.457 |
|  | High | -0.285 | 0.237 | 0.072 |
|  | Age 35-44 |  |  |  |
|  | Unskilled | 0.761 | -0.632 | -0.496 |
|  | Low-medium | -0.813 | 0.669 | 0.542 |
|  | High | -0.547 | 0.459 | 0.346 |
|  | Age 45-54 |  |  |  |
|  | Unskilled | 0.825 | -0.705 | -0.678 |
|  | Low-medium | -0.904 | 0.767 | 0.753 |
|  | High | -0.562 | 0.487 | 0.449 |
|  | Age 55-64 |  |  |  |
|  | Unskilled | 0.851 | -0.770 | -0.766 |
|  | Low-medium | -0.897 | 0.796 | 0.843 |
|  | High | -0.629 | 0.601 | 0.497 |

Skill levels for the use of computers: High = individuals who have carried out 5 or 6 of the computer related activities; Medium =3-4 activities, Low =1-2 activities; Unskilled $=0$ activity. Educational attainment: High $=$ ISCED 5-6; Medium $=$ ISCED 3-4 \& Low= ISCED 0-2.
Source: Information society statistics \& European Labour Force Survey (2007, Eurostat)

Table 8b: Determinants of the level of skills for computer use. (Multinomial logit estimations, base $=$ medium skills, relative risk ratios)

|  | 16-19 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 | 45-49 | 50-64 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| No skills for computer use |  |  |  |  |  |  |  |  |
| Female | $0.463^{* *}$ | 0.631* | $0.755^{*}$ | 0.876 | 0.645*** | 0.953 | 0.819 | 0.917 |
| Low-educated | 1.922 | 4.784** | 2.973*** | 3.276*** | $3.372^{* * *}$ | 3.769*** | 4.456*** | $6.574^{* * *}$ |
| High-educated |  | 0.732 | 0.302*** | 0.415*** | $0.346^{* * *}$ | 0.330*** | $0.563^{* * *}$ | 0.420*** |
| Foreigner | 4.019*** | $7.747^{* * *}$ | $2.714^{* * *}$ | $2.734^{* * *}$ | $2.834^{* * *}$ | $2.590^{* * *}$ | 1.564 | 1.407 |
| Employed | 2.025** | 0.698 | $1.462^{* *}$ | $1.370^{* *}$ | 0.497*** | 0.710*** | $0.577^{* * *}$ | $0.521 * * *$ |
| High skills for computer use |  |  |  |  |  |  |  |  |
| Female | 0.423 *** | 0.590*** | 0.579*** | $0.600^{* * *}$ | 0.434*** | $0.507^{* * *}$ | 0.391*** | $0.329^{* * *}$ |
| Low-educated | $0.529^{* * *}$ | 0.291*** | $0.475^{* * *}$ | 0.382*** | $0.344^{* * *}$ | 0.392*** | 0.648** | $0.373^{* * *}$ |
| High-educated |  | $1.551^{* *}$ | $1.702^{* * *}$ | $1.562^{* * *}$ | $1.746^{* * *}$ | $1.514^{* * *}$ | $2.219^{* * *}$ | $1.487^{* * *}$ |
| Foreigner | 0.572 | 0.533* | 0.509*** | 0.554*** | 0.990 | 0.833 | 0.763 | 1.006 |
| Employed | 0.802 | $0.743^{* *}$ | $0.637^{* * *}$ | 0.810* | 1.266 | 1.337 | 1.148 | $1.354^{* *}$ |

Significant at $1 \%\left({ }^{* * *)}, 5 \%\left({ }^{* *}\right) \& 10 \%(*)\right.$. Source: Encuesta sobre Equipamiento y Uso de Tecnologías
de Información y Comunicación en los Hogares (2007, INE).
Table 9: correlation coefficients between levels of education \& computer skills and productivity and employment rates, by age (EU15 countries, 2007)

|  | Productivity per worker | Productivity per hour | Employment rate | FT Equiv. emp. Rate |
| :---: | :---: | :---: | :---: | :---: |
| Education attainment: |  |  |  |  |
| Low | -0,626 | -0,651 | -0,475 | -0,134 |
| Medium | 0,444 | 0,467 | 0,342 | 0,001 |
| High | 0,540 | 0,556 | 0,405 | 0,284 |
| Computer skills: |  |  |  |  |
| Unskilled | -0,227 | -0,599 | -0,813 | -0,352 |
| Medium-Low | 0,380 | 0,650 | 0,714 | 0,267 |
| High | -0,051 | 0,376 | 0,753 | 0,387 |

Table 10: Estimation of obtaining e-skills by ways in Spain
(Probit estimations, marginal effects, 2007)

|  | FORMAL EDUCATION | $\begin{gathered} \hline \hline \text { COURSES } \\ \text { ON OWN } \\ \text { INICIATIVE } \end{gathered}$ | COURSES ON DEMAND OF EMPLOYER | SELF-STUDY | LEARNING BY DOING | INF. ASSIST |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Female | $\begin{gathered} \hline-0.006 \\ (0.005) \end{gathered}$ | $\begin{gathered} \hline 0.066 * * * \\ (0.006) \end{gathered}$ | $\begin{gathered} \hline-0.009^{*} \\ (0.005) \end{gathered}$ | $\begin{gathered} \hline-0.089 * * * \\ (0.006) \end{gathered}$ | $\begin{gathered} \hline-0.095 * * * \\ (0.009) \end{gathered}$ | $\begin{gathered} \hline-0.046 * * * \\ (0.009) \end{gathered}$ |
| Age 20-24 | $\begin{gathered} -0.072 * * * \\ (0.005) \end{gathered}$ | $\begin{gathered} 0.016 \\ (0.020) \end{gathered}$ | $\begin{gathered} 0.038 \\ (0.029) \end{gathered}$ | $\begin{gathered} -0.061 * * * \\ (0.014) \end{gathered}$ | $\begin{gathered} -0.182 * * * \\ (0.028) \end{gathered}$ | $\begin{gathered} -0.153 * * * \\ (0.023) \end{gathered}$ |
| Age 25-29 | $\begin{gathered} -0.107 * * * \\ (0.004) \end{gathered}$ | $\begin{gathered} 0.059 * * * \\ (0.020) \end{gathered}$ | $\begin{gathered} 0.087 * * * \\ (0.032) \end{gathered}$ | $\begin{gathered} -0.078 * * * \\ (0.013) \end{gathered}$ | $\begin{gathered} -0.342 * * * \\ (0.022) \end{gathered}$ | $\begin{gathered} -0.224^{* * *} \\ (0.020) \end{gathered}$ |
| Age 30-34 | $\begin{gathered} -0.131 * * * \\ (0.004) \end{gathered}$ | $\begin{gathered} 0.099 * * * \\ (0.021) \end{gathered}$ | $\begin{gathered} 0.139 * * * \\ (0.035) \end{gathered}$ | $\begin{gathered} -0.079 * * * \\ (0.012) \end{gathered}$ | $\begin{gathered} -0.373 * * * \\ (0.020) \end{gathered}$ | $\begin{gathered} -0.263 * * * \\ (0.018) \end{gathered}$ |
| Age 35-39 | $\begin{gathered} -0.147 * * * \\ (0.004) \end{gathered}$ | $\begin{gathered} 0.080 * * * \\ (0.020) \end{gathered}$ | $\begin{gathered} 0.179 * * * \\ (0.036) \end{gathered}$ | $\begin{gathered} -0.089 * * * \\ (0.012) \end{gathered}$ | $\begin{gathered} -0.424 * * * \\ (0.018) \end{gathered}$ | $\begin{gathered} -0.323 * * * \\ (0.016) \end{gathered}$ |
| Age 40-44 | $\begin{gathered} -0.159 * * * \\ (0.005) \end{gathered}$ | $\begin{gathered} 0.070 * * * \\ (0.019) \end{gathered}$ | $\begin{gathered} 0.207 * * * \\ (0.038) \end{gathered}$ | $\begin{gathered} -0.094 * * * \\ (0.0129 \end{gathered}$ | $\begin{gathered} -0.448 * * * \\ (0.017) \end{gathered}$ | $\begin{gathered} -0.344^{* * *} \\ (0.016) \end{gathered}$ |
| Age 45-49 | $\begin{gathered} -0.153 * * * \\ (0.004) \end{gathered}$ | $\begin{gathered} 0.036 \\ (0.019) \end{gathered}$ | $\begin{gathered} 0.227 * * * \\ (0.040) \end{gathered}$ | $\begin{gathered} -0.118 * * * \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.480 * * * \\ (0.015) \end{gathered}$ | $\begin{gathered} -0.359 * * * \\ (0.015) \end{gathered}$ |
| Age 50-64 | $\begin{gathered} -0.316 * * * \\ (0.007) \end{gathered}$ | $\begin{gathered} -0.045 * * * \\ (0.015) \end{gathered}$ | $\begin{gathered} 0.189 * * * \\ (0.031) \end{gathered}$ | $\begin{gathered} -0.198 * * * \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.641^{* * *} \\ (0.014) \end{gathered}$ | $\begin{gathered} -0.514^{* * *} \\ (0.014) \end{gathered}$ |
| Foreigner | $\begin{gathered} 0.011 \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.075 * * * \\ (0.011) \end{gathered}$ | $\begin{gathered} -0.058 * * * \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.040 * * * \\ (0.012) \end{gathered}$ | $\begin{gathered} -0.174 * * * \\ (0.018) \end{gathered}$ | $\begin{gathered} -0.110^{* * * *} \\ (0.017) \end{gathered}$ |
| Low-educ. attainment | $\begin{gathered} -0.113 * * * \\ (0.007) \end{gathered}$ | $\begin{gathered} -0.156^{* * *} \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.135 * * * \\ (0.007) \end{gathered}$ | $\begin{gathered} -0.189 * * * \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.350^{* * *} \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.296^{* * *} \\ (0.010) \end{gathered}$ |
| High educ. attainment | $\begin{gathered} 0.115 * * * \\ (0.008) \end{gathered}$ | $\begin{gathered} 0.032 * * * \\ (0.008) \end{gathered}$ | $\begin{gathered} 0.056 * * * \\ (0.007) \end{gathered}$ | $\begin{gathered} 0.123 * * * \\ (0.009) \end{gathered}$ | $\begin{gathered} 0.203 * * * \\ (0.012) \end{gathered}$ | $\begin{gathered} 0.122 * * * \\ (0.012) \end{gathered}$ |
| Manual |  |  | $\begin{gathered} 0.024 * * * \\ (0.009) \end{gathered}$ |  |  |  |
| Non-manual IT |  |  | $\begin{gathered} 0.339 * * * \\ (0.034) \end{gathered}$ |  |  |  |
| Non manual, non-IT |  |  | $\begin{gathered} 0.156 * * * \\ (0.009) \end{gathered}$ |  |  |  |
| N | 16,134 | 16,134 | 16,134 | 16,134 | 16,134 | 16,134 |
| Predicted probability | . 094 | . 178 | . 104 | . 191 | . 560 | . 470 |

[^7]Tecnologías de Información y Comunicación en los Hogares (2007, INE).

Table 11: correlation coefficients between the channels for obtaining computer skills and productivity, TFP and Employment rates by age (EU15 countries, 2007)
$\left.\begin{array}{lccccc} & \begin{array}{c}\text { Productivity } \\ \text { per worker } \\ \mathbf{2 0 0 7}\end{array} & \begin{array}{c}\text { Productivity } \\ \text { per hour } \\ \mathbf{2 0 0 7} \\ \text { (EU15=100) }\end{array} & \begin{array}{c}\text { Var. } \\ \text { Productivity } \\ \text { per hour }\end{array} & \begin{array}{c}\text { Var. } \\ \text { TFP }\end{array} & \begin{array}{c}\text { Employment } \\ \text { rate }\end{array} \\ \text { 1996-2007 }\end{array}\right]$

Source: Information society statistics \& European Labour Force Survey (2007, Eurostat), EU-Klems
(March 2007)

Table 12a: Estimations of school drop-out rates, by gender, native population aged 16-17 years (regional pooled regressions, 1996-2006/8)

|  | Males |  | Females |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (a) | (b) | (a) | (b) |
| (Cohort 16-17 /pop 16-64 low-ed), g | $-.606 * * *$ $(.242)$ | $\begin{gathered} \hline-.652 * * \\ (.295) \end{gathered}$ | $\begin{aligned} & \hline-.776 \\ & (.628) \end{aligned}$ | $\begin{aligned} & \hline-.732^{*} \\ & (.452) \end{aligned}$ |
| Share of low-educated pop. (26_64), g | $\begin{gathered} .104 \\ (1.169) \end{gathered}$ | $\begin{gathered} .668 \\ (.829) \end{gathered}$ | $\begin{gathered} .048 \\ (1.814) \end{gathered}$ | $\begin{gathered} -.068 \\ (1.433) \end{gathered}$ |
| Female activity rate (26-54) | $\begin{aligned} & 1.059 \\ & (.706) \end{aligned}$ | $\begin{gathered} 1.673^{* *} \\ (.779) \end{gathered}$ | $\begin{gathered} .208 \\ (.969) \end{gathered}$ | $\begin{gathered} 1.321 \\ (1.091) \end{gathered}$ |
| Temporary rate, low-ed. 16-19, g | $\begin{aligned} & -.373 \\ & (.543) \end{aligned}$ | $\begin{gathered} .250 \\ (.586) \end{gathered}$ | $\begin{aligned} & 1.076 \\ & (.896) \end{aligned}$ | $\begin{gathered} 1.522 * * * \\ (.598) \end{gathered}$ |
| Share of workers 50-64/total employment | $\begin{aligned} & -.016 \\ & (.187) \end{aligned}$ | $\begin{gathered} .111 \\ (.149) \end{gathered}$ | $\begin{aligned} & -.105 \\ & (.232) \end{aligned}$ | $\begin{gathered} -.139 \\ (.228) \end{gathered}$ |
| Unemployment rate, g | $\begin{aligned} & -.034 \\ & (.106) \end{aligned}$ | $\begin{gathered} -.070 \\ (.094) \end{gathered}$ | $\begin{aligned} & .367 * * \\ & (.171) \end{aligned}$ | $\begin{gathered} .027 \\ (.217) \end{gathered}$ |
| Distribution of employment: |  |  |  |  |
| Share high-tech manufacturing | $\begin{aligned} & -.009 \\ & (.051) \end{aligned}$ |  | $\begin{aligned} & -.009 \\ & (.058) \end{aligned}$ |  |
| Share medium-tech manufacturing | $\begin{aligned} & -.080 \\ & (.237) \end{aligned}$ |  | $\begin{aligned} & -.647 \\ & (.443) \end{aligned}$ |  |
| Share low-tech manufacturing | $\begin{gathered} .554 * * * \\ (.124) \end{gathered}$ |  | $\begin{aligned} & -.105 \\ & (.269) \end{aligned}$ |  |
| Share less intensive knowledge services | $\begin{gathered} .092 \\ (.348) \end{gathered}$ |  | $\begin{gathered} .073 \\ (1.227) \end{gathered}$ |  |
| Share agriculture | $\begin{gathered} .370^{* * *} \\ (.096) \end{gathered}$ |  | $\begin{gathered} .042 \\ (.336) \end{gathered}$ |  |
| Share construction | $\begin{aligned} & .563^{*} \\ & (.313) \end{aligned}$ |  | $\begin{gathered} .335 \\ (.399) \end{gathered}$ |  |
| Share public Administration | $\begin{gathered} .295 \\ (.266) \end{gathered}$ |  | $\begin{gathered} -.200 \\ (.359) \end{gathered}$ |  |
| Share other sectors | $\begin{aligned} & -.079 \\ & (.062) \end{aligned}$ |  | $\begin{aligned} & -.077 \\ & (.079) \end{aligned}$ |  |
| Capital/Output |  | $\begin{gathered} -.196 * * * \\ (.058) \end{gathered}$ |  | $\begin{aligned} & .132 \\ & (.132) \end{aligned}$ |
| ICT Capital/Capital |  | $\begin{gathered} .232 \\ (.194) \end{gathered}$ |  | $\begin{aligned} & -.466 \\ & (.602) \end{aligned}$ |
| Y fitted values | . 174 | . 174 | . 107 | . 108 |
| N | 217 | 183 | 214 | 181 |
| R-squared | . 845 | . 844 | . 808 | . 819 |

Elasticities after regress in the form (d(lny)/d(lnx)) \& standard errors in parenthesis. Weighted regressions (weights: regional population aged 16-17 / national pop. of the same age); exclusions of cell < 30 and clusters by regions for standard errors. g = gender. Source: EPA (Q2). Standard errors are in parentheses. ***, ** and * denote significance at $1 \%, 5 \%$ and $10 \%$ levels, respectively. (a): 1996-2008; (b) 1996-2006.

Sources: EPA (Q2), Contabilidad Regional de España (INE) \& El stock y los servicios del capital en España y su distribución territorial (Fundación BBVA)

Table 12b: Estimations of school drop-out rates, native population aged 18-25 years (regional pooled regressions, 1996-2006/8)

|  | Males |  | Females |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (a) | (b) | (a) | (b) |
| Age 20-21 | .074*** | .073*** | .119*** | .119*** |
|  | (.007) | (.007) | (.009) | (.011) |
| Age 22-23 | .092*** | .090*** | .158*** | .156*** |
|  | (.012) | (.014) | (.015) | (.019) |
| Age 24-25 | .094*** | .092*** | .163*** | .163*** |
|  | (.015) | (.017) | (.018) | (.022) |
| (Cohort age /pop 16-64) low-ed, g | .798*** | .811*** | . $907 * * *$ | . 871 *** |
|  | (.080) | (.076) | (.075) | (.073) |
| Share of low-educated pop. (26_64), g | .599*** | . $579 * * *$ | . 343 | . 401 |
|  | (.183) | (.199) | (.338) | (.392) |
| Female activity rate (26-54) | .267* | . 115 | -. 192 | -. 175 |
|  | (.165) | (.141) | (.195) | (.297) |
| Temporary rate, low-ed. 18-25, g | -. 073 | -. 009 | -.141** | -.121** |
|  | (.060) | (.055) | (.063) | (.064) |
| Share of workers 50-64/total employment | $-.219 * * *$ | --.127* | -. 067 | -. 037 |
|  | (.087) | (.069) | (.237) | (.222) |
| Unemployment rate, g | $.000$ | $.222 * * *$ | $-.035$ | $.297 * *$ |
|  | (.030) | (.069) | (.042) | (.133) |
| Distribution of employment: |  |  |  |  |
| Share high-tech manufacturing | .031*** |  | .029* |  |
|  | (.011) |  | (.017) |  |
| Share medium-tech manufacturing | . 030 |  | . 064 |  |
|  | (.050) |  | (.072) |  |
| Share low-tech manufacturing | .163*** |  | . 104 |  |
|  | (.056) |  | (.093) |  |
| Share less intensive knowledge services | . 158 |  | . 102 |  |
|  | (.138) |  | (.313) |  |
| Share agriculture | .075*** |  | . 014 |  |
|  | (.027) |  | (.054) |  |
| Share construction | .165** |  | . 176 |  |
|  | (.079) |  | (.115) |  |
| Share public Administration | . 026 |  | -.103* |  |
|  | (.050) |  | (.061) |  |
| Share other sectors | $-.006$ |  | $-.027$ |  |
|  | (.012) |  | (.017) |  |
| Capital/Output |  | (.024) |  | $(.045)$ |
| ICT Capital/Capital |  | $-.061 * * *$ |  | -.102** |
|  |  | (.018) |  | (.044) |
| Drop out rates at 16-17 years old | .132** | . 140 | . 171 *** | . $159 * * *$ |
|  | (.061) | (.097) | (.057) | (.062) |
| Y fitted values | . 364 | . 365 | . 239 | . 238 |
| N | 873 | 739 | 858 | 728 |
| R-squared | . 850 | . 862 | . 859 | . 868 |

Elasticities after regress in the form $(\mathrm{d}(\ln y) / \mathrm{d}(\ln x)) \&$ standard errors in parenthesis. Weighted regressions (weights: regional population by age ( 2 in 2 years) / national pop. of the same age); exclusions of cell < 30 and clusters by regions for standard errors. $\mathrm{g}=$ gender. Source: EPA (Q2). Standard errors are in parentheses. ***, ** and * denote significance at $1 \%, 5 \%$ and $10 \%$ levels, respectively. (a): 1996-2008; (b) 1996-2006. Sources: EPA (Q2),
Contabilidad Regional de España (INE) \& El stock y los servicios del capital en España y su distribución territorial (Fundación BBVA)

Table 13: Number of jobs required to have a similar occupational structure/pop. to other EU15 countries (2009Q1)

|  | Thousand of jobs |  |  |  | \% |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| NL | All | Non-manual | Prof. \& techn | Manual | All | Non-manual | Prof. \& techn | Manual |
| DK | 5994 | 6840 | 5299 | -1848 | 27 | 60 | 83 | -24 |
| SE | 3680 | 6216 | 4840 | -1237 | 27 | 55 | 76 | -16 |
| FI | 2540 | 3504 | 4031 | -1674 | 20 | 47 | 63 | -22 |
| UK | 3131 | 4870 | 3501 | -1006 | 13 | 31 | 55 | -13 |
| DE | 2867 | 3530 | 2944 | -1785 | 17 | 43 | 50 | -24 |
| BE | 322 | 2701 | 2415 | -2327 | 15 | 31 | 46 | -9 |
| FR | 1298 | 2261 | 2070 | -824 | 7 | 24 | 38 | -31 |
| AT | 3316 | 3319 | 2010 | -33 | 18 | 20 | 33 | -11 |
| IE | 796 | 3025 | 1587 | -2267 | 4 | 27 | 32 | 0 |
| IT | -1016 | 107 | 681 | -1035 | -5 | 1 | 11 | -30 |
| GR | 72 | 414 | 259 | -220 | 0 | 4 | 4 | -14 |
| PT | 2069 | -75 | -699 | 2162 | 11 | -1 | -11 | 28 |

Sources: European Labour Force Survey (Eurostat)

Table 14: Share of the population with tertiary education well-matched,
mismatched \& non-employed
(\%, EU15 countries, 2007, 15-64 years)

|  |  | Total |  |  | Men |  |  | Women |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Well-match | Mismatch | Non-emp. | Well-match | Mismatch | Non-emp. | Well-match | Mismatch | Non-emp. |
| Sweden | 76.3 | 12.9 | 10.8 | 76.0 | 10.8 | 13.2 | 76.4 | 15.2 | 8.4 |
| Denmark | 75.2 | 13.1 | 11.7 | 76.9 | 12.1 | 10.9 | 73.7 | 13.6 | 12.7 |
| Netherland | 74.8 | 13.1 | 12.2 | 78.0 | 15.7 | 6.3 | 71.2 | 11.0 | 17.8 |
| Portugal | 72.7 | 13.2 | 14.1 | 77.8 | 15.3 | 6.9 | 69.4 | 11.6 | 19.0 |
| Finland | 70.4 | 13.1 | 16.5 | 76.4 | 13.2 | 10.5 | 66.0 | 13.4 | 20.6 |
| Germany | 68.6 | 15.3 | 16.1 | 69.5 | 11.6 | 18.9 | 67.4 | 18.3 | 14.3 |
| Italy | 67.9 | 18.2 | 13.9 | 76.5 | 21.8 | 1.6 | 60.7 | 15.0 | 24.2 |
| Austria | 67.6 | 18.6 | 13.8 | 67.9 | 14.9 | 17.1 | 67.2 | 22.2 | 10.6 |
| UK | 67.4 | 18.8 | 13.8 | 72.1 | 23.0 | 4.9 | 62.6 | 14.1 | 23.2 |
| Belgium | 65.6 | 18.7 | 15.8 | 70.9 | 17.0 | 12.1 | 60.9 | 20.2 | 19.0 |
| Greece | 65.3 | 20.1 | 14.5 | 69.0 | 25.3 | 5.7 | 61.5 | 14.1 | 24.4 |
| France | 62.7 | 19.8 | 17.5 | 68.0 | 17.7 | 14.3 | 58.1 | 22.1 | 19.8 |
| Ireland | 58.9 | 28.0 | 13.2 | 62.7 | 28.9 | 8.5 | 55.7 | 27.3 | 17.1 |
| Spain | 53.9 | 29.2 | 16.9 | 56.3 | 32.1 | 11.6 | 51.5 | 26.4 | 22.0 |
| EU15 | 65.6 | 19.4 | 15.0 | 69.3 | 19.8 | 10.9 | 61.9 | 19.1 | 19.0 |

[^8]Table 15a: Share of well-matched, mismatched \& non-employed high educated population, by age and gender, ( graduates < 65 years old)

| trim |  | Men |  |  |  | Women |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 1996Q2 | 2001Q2 | 2007Q2 | 2009Q2 | 1996Q2 | 2001Q2 | 2007Q2 | 2009Q2 |
| < 30 years | Well-matched | 37.6 | 39.7 | 45.3 | 44.9 | 30.2 | 32.9 | 37.6 | 39.6 |
|  | Mismatched | 20.4 | 31.1 | 37.9 | 28.5 | 22.0 | 34.9 | 41.1 | 34.8 |
|  | Non-employed | 42.0 | 29.1 | 16.8 | 26.6 | 47.7 | 32.2 | 21.4 | 25.7 |
| 30-39 years | Well-matched | 66.9 | 62.4 | 54.7 | 56.6 | 49.5 | 50.2 | 46.9 | 45.4 |
|  | Mismatched | 22.3 | 30.4 | 38.5 | 33.9 | 26.1 | 29.1 | 38.2 | 37.6 |
|  | Non-employed | 10.7 | 7.3 | 6.9 | 9.5 | 24.4 | 20.7 | 14.9 | 17.1 |
| 40-49 years | Well-matched | 75.5 | 72.8 | 66.4 | 66.5 | 55.7 | 56.9 | 53.9 | 54.6 |
|  | Mismatched | 22.0 | 23.2 | 29.4 | 25.8 | 27.9 | 26.7 | 33.0 | 31.9 |
|  | Non-employed | 2.5 | 4.0 | 4.2 | 7.7 | 16.5 | 16.4 | 13.1 | 13.4 |
| >= 50 years | Well-matched | 65.7 | 68.4 | 63.9 | 66.2 | 51.7 | 49.0 | 50.8 | 52.0 |
|  | Mismatched | 18.6 | 19.9 | 20.8 | 19.7 | 14.8 | 24.2 | 24.0 | 23.4 |
|  | Non-employed | 15.7 | 11.8 | 15.3 | 14.2 | 33.5 | 26.8 | 25.2 | 24.6 |

Table 15b: Share of well-matched, mismatched \& non-employed high educated population, by age and gender, (diploma \& university graduates, \%/employment,
graduates < 65 years old)


[^9]Table 16: Trends of the skill premium in Spain

## Skill premium

|  | $\underline{\mathbf{1 9 9 5}}$ | $\underline{\mathbf{2 0 0 2}}$ | $\underline{\mathbf{2 0 0 6}}$ | $\underline{\left.\mathbf{2 0 0 6} \boldsymbol{*}^{*}\right)}$ |
| :--- | :--- | :--- | :--- | :--- |
| Primera etapa secundaria | 0.010 | 0.006 | 0.021 | 0.021 |
| Bachiller | 0.222 | 0.188 | 0.150 | 0.152 |
| FP Grado medio | 0.093 | 0.100 | 0.101 | 0.094 |
| FP Grado superior mismatched | 0.145 | 0.115 | 0.116 | 0.108 |
| FP Grado superior well-matched | 0.343 | 0.312 | 0.259 | 0.259 |
| Diplomado mismatched | 0.301 | 0.277 | 0.238 | 0.239 |
| Diplomado well-matched | 0.610 | 0.568 | 0.508 | 0.564 |
| Titulado superior mismatched | 0.408 | 0.369 | 0.331 | 0.355 |
| Titulado superior well-matched | 0.803 | 0.777 | 0.705 | 0.727 |
| (Constant) | 1.668 | 1.728 | 1.732 | 1.528 |

\% workers well-matched

|  | $\underline{\mathbf{1 9 9 5}}$ | $\underline{\mathbf{2 0 0 2}}$ | $\underline{\mathbf{2 0 0 6}}$ | $\underline{\mathbf{2 0 0 6} \boldsymbol{*}^{*}}$ |
| :--- | :--- | :--- | :--- | :--- |
| FP grado superior | $\mathbf{2 5 . 7}$ | $\mathbf{3 5 . 6}$ | $\mathbf{3 2 . 1}$ | 34.5 |
| Diplomados | 47.9 | 41.6 | 33.7 | 47.6 |
| Titulados superiores | 60.8 | 48.7 | 41.2 | 50.4 |

Note: Firm size >= 10 workers. (*) All firm sizes.
Source: Encuesta de Estructura Salarial, 1995, 2002, 2006.

Table 17: Probability of mismatch \& skill premium (University graduates)

|  | Probability to be adjusted <br> (Probit estimations) |  |  |  | Ln hourly wage <br> (OLS) |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1995 | 2002 | 2006 | $2006^{*}$ | 1995 | 2002 | 2006 |  |
| Share of low educated at | -0.071 | -0.142 | -0.203 | -0.244 | -0.159 | -0.198 | -0.203 |  |
| the firm | $(0.019)$ | $(0.017)$ | $(0.014)$ | $(0.013)$ | $(0.017)$ | $(0.014$ | $(0.011)$ |  |
|  |  |  |  |  |  |  |  |  |
| Share of low educated at | -0.087 | -0.154 | -0.209 | -0.250 | -0.189 | -0.220 | -0.218 |  |
| the firm | $(0.020$ | $(0.017)$ | $(0.014)$ | $(0.013)$ | $(0.0189$ | $(0.015)$ | $-0.012)$ |  |
| Share of workers aged | 0.110 | 0.113 | 0.059 | 0.061 | 0.206 | 0.202 | 0.155 |  |
| 50-64 | $(0.033$ | $(0.029)$ | $(0.022)$ | $(0.018)$ | $(0.030)$ | $(0.025)$ | $(0.018)$ |  |
|  |  |  |  |  |  |  | $(0.186$ |  |
| Share of low educated at | -0.073 | -0.145 | -0.200 | -0.247 | -0.158 | -0.190 | -0.195 |  |
| the firm | $(0.019)$ | $(0.017)$ | $(0.014)$ | $(0.013)$ | $(0.017)$ | $(0.015)$ | $-0.012)$ |  |
| Share of permanent | -0.053 | -0.025 | 0.026 | -0.026 | 0.013 | 0.072 | 0.077 |  |
| contracts | $(0.024)$ | $(0.023)$ | $(0.019)$ | $(0.014)$ | $(0.022)$ | $(0.020)$ | $(0.015)$ |  |

Note: sample restricted to firm size >= 10 workers. (*) All firm sizes.
Source: Encuesta de Estructura Salarial 1995, 2002, 2006.

Table 18: Estimations of well-matched rates of University graduates aged 22-35 years, (regional pooled regressions, 1996-2006/8)

|  | Males |  | Females |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (a) | (b) | (a) | (b) |
| Age 24-25 | .060*** | .060*** | .074*** | .072*** |
|  | (.009) | (.011) | (.005) | (.007) |
| Age 26-27 | .135*** | .137*** | .125*** | . 121 *** |
|  | (.012) | (.014) | (.006) | (.008) |
| Age 28-29 | .168*** | .170*** | .142*** | .137*** |
|  | (.011) | (.014) | (.006) | (.007) |
| Age 30-31 | .174*** | .169*** | .135*** | .131*** |
|  | (.009) | (.010) | (.006) | (.007) |
| Age 32-33 | . 175 *** | .171*** | .134*** | .133*** |
|  | (.006) | (.006) | (.004) | (.003) |
| Age 34-35 | .180*** | .177*** | .131*** | .132*** |
|  | (.006) | (.006) | (.004) | (.005) |
| (Cohort age /pop 16-64) univ. graduates, g | -.349*** | -. 309 *** | -. $374 * * *$ | -. $258 * * *$ |
|  | (.061) | (.083) | (.061) | (.094) |
| Share of pop. with medium educ (26_64), g | . 021 | -. 301 | 391** | . 266 |
|  | (.203) | (.230) | (.165) | (.204) |
| Share of workers 50-64/total employment | . 045 | $.326$ | $-.691^{* * *}$ | $-.216$ |
|  | (.310) | (.380) | (.157) | (.156) |
| Unemployment rate, g | -. 097 | -.147* | -.090** | $-.224^{* * *}$ |
|  | (.070) | (.084) | (.045) | $(.092)$ |
| Distribution of employment: |  |  |  |  |
| Share high-tech manufacturing | -. 014 |  | -. 053 *** |  |
|  | (.030) |  | (.016) |  |
| Share medium-tech manufacturing | -. 073 |  | -. $379 * * *$ |  |
|  | (.118) |  | (.096) |  |
| Share low-tech manufacturing | -. 150 |  | -. 096 |  |
|  | (.108) |  | (.084) |  |
| Share less intensive knowledge services | -. 285 |  | -. 173 |  |
|  | (.323) |  | (.150) |  |
| Share agriculture | -. 044 |  | -. 044 |  |
|  | (.050) |  | (.030) |  |
| Share construction | -. 087 |  | -. 115 |  |
|  | (.153) |  | (.119) |  |
| Share public Administration | -.269*** |  | -. 187 *** |  |
|  | (.111) |  | (.043) |  |
| Share other sectors | $\begin{aligned} & -.048 \\ & (.025) \end{aligned}$ |  | $-.030^{* *}$ |  |
| Capital/Output |  | .215*** |  | .214*** |
|  |  | (.072) |  | (.058) |
| ICT Capital/Capital |  | $-.421$ |  | $\text { . } 625 * *$ |
|  |  | (.266) |  | (.327) |
| Y fitted values | . 406 | . 538 | . 331 | . 473 |
| N | 1488 | 1243 | 1512 | 1278 |
| R-squared | . 729 | . 279 | . 698 | . 337 |

Elasticities after regress in the form $(\mathrm{d}(\operatorname{lny}) / \mathrm{d}(\ln x)) \&$ standard errors in parenthesis. Weighted regressions (weights: regional population aged 16-17 / national pop. of the same age); exclusions of cell < 30 and clusters by regions for standard errors. $g=$ gender. Source: EPA (Q2). Standard errors are in parentheses. ${ }^{* * *}$, ** and ${ }^{*}$ denote significance at $1 \%, 5 \%$ and $10 \%$ levels, respectively. (a): 1996-2008; (b) 1996-2006.

Sources: EPA (Q2), Contabilidad Regional de España (INE) \& El stock y los servicios del capital en España y su distribución territorial (Fundación BBVA)

Table 19: Estimations of lifecycle learning rates of population aged 36-49 years, (regional pooled regressions, 1996-2008)

|  | Males |  | Females |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (a) | (b) | (a) | (b) |
| Age 38-39 | $\begin{gathered} \hline-.002 * * \\ (.001) \end{gathered}$ | $\begin{gathered} \hline .003 * * * \\ (.001) \end{gathered}$ | $\begin{gathered} \hline .007 * * * \\ (.001) \end{gathered}$ | $\begin{gathered} -.006 * * * \\ (.002) \end{gathered}$ |
| Age 40-41 | $\begin{gathered} -.005^{* * *} \\ (.001) \end{gathered}$ | $\begin{gathered} -.007 * * * \\ (.002) \end{gathered}$ | $\begin{gathered} -.013 * * * \\ (.003) \end{gathered}$ | $\begin{gathered} -.013 * * * \\ (.003) \end{gathered}$ |
| Age 42-43 | $\begin{gathered} -.009^{* * *} \\ (.002) \end{gathered}$ | $\begin{gathered} -.010^{* * *} \\ (.002) \end{gathered}$ | $\begin{gathered} -.020 * * * \\ (.002) \end{gathered}$ | $\begin{gathered} -.020 * * * \\ (.002) \end{gathered}$ |
| Age 44-45 | $\begin{gathered} -.013^{* * *} \\ (.001) \end{gathered}$ | $\begin{gathered} -.013 * * * \\ (.001) \end{gathered}$ | $\begin{gathered} -.025 * * * \\ (.002) \end{gathered}$ | $\begin{gathered} -.025 * * * \\ (.002) \end{gathered}$ |
| Age 46-47 | $\begin{gathered} -.017 * * * \\ (.002) \end{gathered}$ | $\begin{gathered} -.016 * * * \\ (.002) \end{gathered}$ | $\begin{gathered} -.030^{* * * *} \\ (.002) \end{gathered}$ | $\begin{gathered} -.029 * * * \\ (.002) \end{gathered}$ |
| Age 48-49 | $\begin{gathered} -.019^{* * *} \\ (.002) \\ \hline \end{gathered}$ | $\begin{gathered} -.020 * * * \\ (.002) \end{gathered}$ | $\begin{gathered} -.036 * * * \\ (.003) \end{gathered}$ | $\begin{gathered} -.034 * * * \\ (.002) \end{gathered}$ |
| Share of low-educated workers (26_64) | $\frac{-.845^{* * *}}{(.238)}$ | $\frac{-.832 * * *}{(.166)}$ | $\frac{-.728 * * *}{(.175)}$ | $\frac{-.922^{* * *}}{(.188)}$ |
| Share of workers 50-64/total employment | $\begin{aligned} & .354^{*} \\ & (.190) \end{aligned}$ | $\frac{.608^{* * *}}{(.201)}$ | $\frac{.472 * * *}{(.101)}$ | $\frac{.691^{* * *}}{(.157)}$ |
| Unemployment rate, g | $\begin{aligned} & -.011 \\ & (.033) \end{aligned}$ | $\begin{gathered} .015 \\ (.057) \end{gathered}$ | $\begin{aligned} & -.020 \\ & (.028) \end{aligned}$ | $\begin{aligned} & -.072 \\ & (.047) \end{aligned}$ |
| Distribution of employment: |  |  |  |  |
| Share high-tech manufacturing | $\begin{gathered} -.035^{*} \\ (.021) \end{gathered}$ |  | $\begin{gathered} -.030^{*} \\ (.017) \end{gathered}$ |  |
| Share medium-tech manufacturing | $\begin{aligned} & -.165 \\ & (.106) \end{aligned}$ |  | $\begin{gathered} -.158^{*} \\ (.086) \end{gathered}$ |  |
| Share low-tech manufacturing | $\begin{gathered} .001 \\ (.120) \end{gathered}$ |  | $\begin{aligned} & -.008 \\ & (.093) \end{aligned}$ |  |
| Share less intensive knowledge services | $\begin{aligned} & -.237 \\ & (.379) \end{aligned}$ |  | $\begin{aligned} & -.204 \\ & (.310) \end{aligned}$ |  |
| Share agriculture | $\begin{gathered} -.017 \\ (.067) \end{gathered}$ |  | $\begin{aligned} & -.021 \\ & (.055) \end{aligned}$ |  |
| Share construction | $\begin{aligned} & -.201^{*} \\ & (.108) \end{aligned}$ |  | $\begin{gathered} -.250^{* *} \\ (.108) \end{gathered}$ |  |
| Share public Administration | $\begin{gathered} -.274^{* * *} \\ (.065) \end{gathered}$ |  | $\begin{gathered} -.211 * * * \\ (.069) \end{gathered}$ |  |
| Share other sectors | $\begin{aligned} & -.018 \\ & (.019) \end{aligned}$ |  | $\begin{aligned} & -.011 \\ & (.017) \end{aligned}$ |  |
| Capital/Output |  | $\begin{aligned} & -.008 \\ & (.046) \end{aligned}$ |  | $\begin{aligned} & -.021 \\ & (.042) \end{aligned}$ |
| ICT Capital/Capital |  | $\begin{aligned} & -.369 \\ & (.239) \end{aligned}$ |  | $\begin{aligned} & -428^{* *} \\ & (.203) \end{aligned}$ |
| N | 1,528 | 1,290 | 1,530 | 1,294 |
| R-squared | 0.960 | 0.960 | 0.953 | 0.955 |

Elasticities after regress in the form $(\mathrm{d}(\operatorname{lny}) / \mathrm{d}(\ln x)) \&$ standard errors in parenthesis. Weighted regressions (weights: regional population by age ( 2 in 2 years 9 / national pop. of the same age); exclusions of cell < 30 and clusters by regions for standard errors. $\mathrm{g}=$ gender. Source: EPA (Q2). Standard errors are in parentheses. ***, ** and * denote significance at $1 \%, 5 \%$ and $10 \%$ levels, respectively. (a): 1996-2008; (b) 1996-2006. Sources: EPA (Q2),
Contabilidad Regional de España (INE) \& El stock y los servicios del capital en España y su distribución territorial (Fundación BBVA)

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[^1]:    Source: European Labour Force Survey (Eurostat).

[^2]:    ${ }^{1}$ The annual growth rate of the non-ICT capital service in Spain (4.27) was almost twice the EU15 average (2.27) and U.S. (2.15) in the period 1995-2005, although the opposite has occurred with the ICT capital services: 10.8 versus 12.28 and 13.57 , respectively (EU-Klems database). Using the Level GGDC Productivity database (see Inklaar, R. \& M. Timmer, 2008) we can observe that compared with a country like U.S., Spain stands out for its low level of Non-ICT capital services per hour worked in the market economy ( 0.8 , with U.S. $=1$ ) and that, on the other hand Italy has a higher ratio to U.S. (1.26). But what both countries share with other Southern European countries is a very low capital services per hour worked (o.23), half of ratio of Finland, Austria and France and even further from other EU countries).

[^3]:    Sources: Information society statistics \& European Labour Force Survey (Eurostat)

[^4]:    ${ }^{2}$ The proportion of people aged 25 to 64 with lower educational background than the postcompulsory secondary education has fallen about 17 pp (from 58.4 to $41.5 \%$ ) between 1996 and 2008. However, the Spanish population with low education is among the highest in Europe (with Portugal, Italy and Greece), because practically all countries have reduced this proportion.

[^5]:    ${ }^{3}$ The cohort size is computed as in Welch (1979), normalizing by the size of the population The proportion of group members at each age cohort is smoothed by computing a moving average with inverted V weights: $c(x)=\sum_{I=-2}^{2} \alpha_{i} n_{x+i}$, where $\mathrm{n}_{\mathrm{x}}$ is the fraction of those in the group who are in their xth year of work experience. The $\alpha$ weights are: $\alpha=3(3,2,1,2,3)$. For age 1617 , the distribution of $\alpha$ is truncated and remaining weights are scaled accordingly to sum to one.

[^6]:    ${ }^{4}$ In this paper we opt for an objective measure of mismatch, which simply compares the educational level of the person with his occupation, following the National classification of occupations that distinguishes between occupations of Diploma and university graduates. Alternative subjective measures validate this classification. See, for example, the results implicit in the Encuesta de Calidad de Vida en el Trabajo, 2006.

[^7]:    Other control variables: children under 16 years old, municipality size. Reference age: 16-19. Significant at $1 \%$ (***), $5 \%$ (**) \& $10 \%$ (*). Source: Encuesta sobre Equipamiento y Uso de

[^8]:    Sources: European Labour Force Survey (Eurostat)

[^9]:    Source: EPA (INE)

