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## The “dynamic” of job competition during the ICT revolution

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## La «dynamique » de la sur-éducation durant la révolution des NTIC

**Résumé :** Ce papier cherche à analyser l'impact des institutions du marché du travail sur l'évolution de la sur-éducation, des inégalités face au chômage et à la stabilité de l'emploi lors du processus de polarisation des postes de travail lié à la diffusion des nouvelles technologies de la communication et de l'information (NTIC). Sur la base de données microéconomiques, nous présentons un ensemble de faits stylisés caractérisant les évolutions des marchés du travail des pays occidentaux. Nous cherchons ensuite à expliquer ces régularités à l'aide d'un modèle de créations-destructions d'emploi à la Mortensen-Pissarides (1994) dans lequel les individus sont hétérogènes de part leurs niveaux initiaux d'éducation. Nous montrons alors que la segmentation du marché du travail entre les individus ayant le niveau d'éducation minimal pour effectuer des tâches cognitives (liées à l'utilisation des nouvelles technologies) et les autres offreurs de travail est endogène. Ainsi, dans une première phase, la hausse de la productivité nette des coûts d'installation liée aux NTIC permet à des individus ayant un niveau moyen d'éducation d'accéder à des nouveaux postes. Toutefois, même si les coûts d'installation liés aux NTIC baissent, l'accroissement de productivité induit par ce progrès technologique accroît le coût du travail via l'indexation des allocations chômage sur la productivité moyenne. Nous montrons alors que le degré d'indexation des allocations chômage est un paramètre clé pour expliquer la dynamique de polarisation des emplois et l'accroissement de la sur-éducation. Nous évaluons également l'impact de cette règle d'indemnisation du chômage sur la stabilité de l'emploi et la taille des deux segments du marchés du travail et les taux de chômage associés à chaque niveau de diplôme.

**Mots clés :** changement technologique, sur-éducation, créations-destructions d'emploi, agents hétérogènes.

# The “dynamic” of job competition during the ICT revolution.

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## Abstract

Our paper seeks to gain insights on the effect of labor market institutions on the evolution of overeducation (job competition), unemployment inequalities and job instability during the polarization process of the labor market fostered by the diffusion of novel technologies. Based on micro data, we first present some stylized facts characterizing the occidental countries' labor markets. We then develop an endogenous job destruction framework à la Mortensen and Pissarides (1994) where each individual is endowed with a given ability level. The process of contact between the set of heterogeneous workers and firms is represented by a traditional matching function. The segmentation of the labor market between workers having the required ability to occupy cognitive jobs (where novel technologies are used) and the rest of the workers occupying simple jobs is endogenously determined. Firms offering a cognitive job support a set up cost but ICT are assumed to improve their productivity. When simulated the model manages to reproduce the U-shaped path followed by the ability requirements needed in cognitive positions as ICT got increasingly diffused. Furthermore, we also draw conclusions concerning the evolution of job stability, the size of each labor market segment and the unemployment rates.

*Keywords:* technological change, overeducation, job turnover, heterogeneous agents

*JEL:* J23, J24, J63, L23, O33

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# 1 Introduction

The introduction and diffusion of information and communication technologies (ICT) over the past thirty years can be understood in two stages. Firstly, during the nineties, the initial adoption of novel technologies was associated with an increase in the relative demand for skilled labor (non production workers) with respect to that of unskilled (production workers) in what became widely known as the skill biased technological change (SBTC) hypothesis (see Berman et al. (1994), Machin and Van Reenen (1998) or Caroli and Van Reenen (2001)). Secondly, more recent studies considering the whole period 1980-2000 (see Autor et al. (2003) for the U.S., Goos and Maning (2003) for U.K., Spitz-Oener (2006) for Germany or Maurin and Thesmar (2005) for France) find that novel technologies have progressively replaced labor input in manual and cognitive routine positions (see table 1 for a definition of the tasks) while complementing non routine cognitive positions (the relationship with respect to non routine manual jobs is more ambiguous). This task biased technological change (TBTC) fosters a progressive polarization of the labor market between “lousy and lovely jobs” (Goos and Maning (2003)). Furthermore, since non routine cognitive jobs are normally implemented by high-skilled workers, the share of this type of labor increases whereas the one of medium-skilled workers, normally associated to routine positions, decreases.

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**Types of positions**

<b>Cognitive/Complex positions</b>		<b>Manual/Simple positions</b>	
Routine	Non Routine	Routine	Non Routine
Workers carry out a limited and well-defined set of cognitive activities, that can be accomplished following explicit rules	Problem-solving and communication activities	Workers carry out a limited and well-defined set of manual activities, that can be accomplished following explicit rules	Workers carry out manual activities that could not be accomplished following explicit rules

Table 1: Definition of the various types of positions.

In sum, the adoption and diffusion of novel technologies follows two stages: in the first one, SBTC is enough to understand the labor market dynamics since there is simply a relative increase in the share of qualified labor. In a second stage, we observe a decline in the share of labor input in routine tasks, generally occupied by medium-skilled workers. Because the ability

requirements to occupy non routine cognitive positions are higher than those needed in routine cognitive positions, the average ability found in cognitive (complex) jobs increases.

The adoption and progressive diffusion of ICT is then associated to a kind of U-shaped evolution in the skill level required in cognitive positions: initially, only very high qualified labor had access to cognitive positions. By means of a learning-by-doing process, these high qualified workers realized that many of the tasks could be routinized and implemented by medium qualified labor. The demand for medium- and high-skilled workers was then increased. Finally, in more recent years, there seems to have been a progressive substitution of medium-skilled by computer capital whereas the demand for highly qualified labor pursues its upturn.

The objective of this paper is to explain the transition between these two labor market dynamics (SBTC vs. TBTC) observed along the ICT revolution. Our thesis is that labor market institutions, and more particularly unemployment benefits (UB), by introducing a source of wage rigidity, induce a sharp bias against medium-skilled workers as novel technologies become increasingly diffused. We start distinguishing between complex jobs and simple jobs. The formers correspond to all cognitive jobs (routine and non routine), whereas simple jobs stand for all manual positions (routine and non routine). The idea is the following: during the ICT revolution, people having a high ability level and occupying a cognitive position, benefit from a more important increase in their productivity than in their wage. For these workers, novel technologies promote a higher job stability and labor demand since wage rigidities are compensated by their abilities. Because these high-skilled workers normally develop non routine cognitive tasks, the demand for this type of tasks rises. In contrast, workers employed in cognitive jobs but having a middle ability level enjoy from a larger increase in their wages than in their productivity. Middle skilled labor input becomes then relatively more expensive, which increases job destruction and reduces the labor demand for these ability slots, which are normally affected to routine cognitive tasks. This process leads middle skilled workers to direct their search to the simple job market segment (manual tasks). The increase of job competition in the simple segment constitutes then the counterpart of the job polarization process, which is taking place via an adjustment of routine positions.

We develop an original theoretical model inspired in Mortensen and Pissarides (1994) and show that as the relative price of ICT with respect to labor falls, skill requirements in cognitive positions increase. By an endogenous segmentation of the labor market between workers having

the required skill level to occupy a cognitive position and the rest of the workers, our model explains why medium-skilled workers were forced to search for simple manual jobs, increasing job competition in this labor market segment and exacerbating the overeducation phenomenon<sup>1</sup>.

The originality of our approach is to focus on the role of labor market institutions when explaining the labor market dynamics along the ICT revolution. During this period, many European countries were characterized by an increasing unemployment insurance. This policy constitutes for firms like a tax on labor wages, which favors the increase in the minimum skill level required to fill cognitive positions (the higher productivity associated to high skill workers should compensate the increased wage). We abstract from the factor substitution relationship between computer capital and labor input in routine tasks proposed by Autor et al. (2006) using an aggregate production function and assume a one job-one firm setup. Our framework can be viewed as a complement to Autor et al. (2003), Maurin and Thesmar (2005) or Autor et al. (2006) where, on the contrary, labor market institutions are omitted. Concerning job competition, we extend the studies of Gautier (2002) and Dolado et al. (2000) where the segmentation of the labor market is completely exogenous, and also the framework presented in Albrecht and Vroman (2002), where the ability level of the workers does not play any role in this segmentation. Because the minimum skill requirement to occupy a cognitive position (which determines the segmentation of the labor market) has followed a non-monotonous path, we need to overcome these models. Furthermore, in all of them separation rates are systematically exogenous. Mortensen and Pissarides (1999) introduce endogenous job destruction but their model predicts an equilibrium characterized by an infinite number of labor market segments perfectly independent between them, therefore job competition issues are ignored.

Our paper goes a step further and considers an endogenous job destruction framework where each individual is endowed with a given ability level and where workers with different skill levels compete for identical jobs. Contrarily to Gautier (2002), Dolado et al. (2000) or Albrecht and Vroman (2002), the segmentation of the labor market between workers having the required ability to occupy cognitive jobs (where novel technologies are used) and the rest of the workers

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<sup>1</sup>Recent empirical work suggests that the proportion of “overqualified” workers is far from negligible although hard to evaluate. Hartog (2000) collects empirical results from various studies about the level of job competition (“overeducation”) in several EU countries. Depending on the methodology used and the country surveyed, this overeducation is estimated to be between 10% and 30% during the first half of the nineties. Moreover, they also show that overeducation increased over the last decades in most EU countries. See also Forgeot and Gautié (1997), and Walker and Zhu (2005) for French and UK data, respectively.

occupying simple jobs is endogenously determined. And contrarily to Mortensen and Pissarides (1999) we introduce job competition. The paper manages to reproduce the U-shaped path followed by the skill requirements demanded by firms in cognitive positions as novel technologies got progressively diffused. This trend yields an increased job competition in the simple segment, since workers that initially had the necessary skills to occupy complex jobs, do not longer qualify for them and are forced to look for simple jobs. Our theoretical framework, allows us to draw conclusions concerning the effect of biased technological shocks on labor flows, overeducation, job creation and destruction of simple (manual) and complex (cognitive) jobs.

The paper is organized as follows. The following section presents some stylized facts observed in the French labor market over the past decades. France is characterized by an important employment protection and unemployment benefits which have been increasing over the past decades. Because we seek to analyze the impact of labor market institutions in the transition from SBTC to TBTC, the French case constitutes an appropriate reference. We will use it for both, the empirical section and the numerical simulations. Section 3 describes our theoretical framework, its assumptions as well as the agents behavior. The steady state equilibrium is described in section 4 and the effects of a biased technological shock in section 5. Numerical simulation are implemented in section 6. Section 7 concludes.

## 2 Stylized facts

The objective of this section is to describe the evolution of labor input by type of task<sup>2</sup> along the ICT revolution. We use the French Complementary Survey on Working Conditions for 1984, 1991, 1998 and 2005. This survey is conducted every seven years on a representative sample of 21000 employed workers interviewed by the Labor Force Survey. The Complementary Survey on Working Conditions covers four fields of interest: *(i)* organization and timetable of working days, *(ii)* workplace organization and job content, *(iii)* working risks, and *(iv)* degree of harmfulness of the job. We dispose therefore of rich information concerning the use of new technologies by the workers as well as some information on the tasks they implement. Furthermore, when matched with the Labor Force Survey we also obtain data on the main activity of the individual

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<sup>2</sup>See appendix A for details on the variables included in each type of task. The number of years of schooling is given by the variables diploma1 to diploma5, where diploma1 stands for zero years and diploma5 for a university diploma (diploma2-diploma4 stand for other basic and intermediate diplomas).

during the survey week, seniority at a job, occupation, wage, size of the firm, age, marital status, number of children, education, nationality and so forth.

## 2.1 Cognitive tasks and overeducation

The transition from a skill biased to a task biased technological progress should be reflected in an U-shaped evolution of skill requirements in cognitive positions. This non monotonous path implies that people that could initially occupy cognitive positions do not longer qualify for them in the last years of the ICT revolution. These medium-skilled workers are then forced to search in the simple segment where they are overeducated and they enter in competition with low-skilled workers.

To test the U-shaped hypothesis it seems interesting to analyze the evolution of overeducation over the past decades. Overeducation is defined as having an actual schooling greater than required by the job. To measure it we use the method of “realized matches”<sup>3</sup>, that is, required education is derived from what workers in the respondent’s job or occupation usually have attained (the mean or the mode of the distribution).

Our descriptive statistics must consider the evolution over the past years of the labor force composition employed in cognitive tasks. To this end, the following tables take as reference the diploma held by the median worker of the aggregate economy<sup>4</sup>. This relative measure adjusts for the increasing trend in the median diploma. In 1984 the median worker had a primary education diploma, whereas in 1991, 1998 and 2005 the median worker attained already a secondary school diploma, underlining the importance of the skill-upgrading process lived by the labor force during this period.

We claim that cognitive positions are selective if the required abilities are above the median diploma of the aggregate economy. The first and second columns of table 2 correspond, respec-

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<sup>3</sup>In the literature of overeducation required education has been measured in 3 different ways:

1. From job analysis: Professional job analysts specify the required level of education for the job titles in an occupational classification. This method requires systematic updates, which is actually very rare.
2. From workers self-assessment: The worker specifies the education required for the job. The drawback of this method is that workers tend to overestimate their skills with respect to those required by the job.
3. From realized matches.

<sup>4</sup>The results do not change if we take the diploma of the mean worker of the aggregate economy as the reference.



tively, to the proportion of workers occupying a cognitive position or being recruited in these positions and having a diploma above the median worker in 1984, 1991, 1998 and 2005. The third column displays the proportion of workers using a computer at their job.

	Proportion of employed workers in cognitive positions with a diploma above the median	Proportion of youth entries in cognitive positions with a diploma above the median	Proportion of computer users
1984	66.63%	75%	11.10%
1991	45.17%	50%	18.17%
1998	50.87%	60%	41.05%
2005	62.40%	65% <sup>1</sup>	59.61%

Youth entries refer to workers having less than 30 years old.

<sup>1</sup> Due to data limitations with the Complementary Survey on Working Conditions 2005, the proportion of youth entries in this year refers to workers having less than five years of seniority.

Table 2: Skill requirements in cognitive positions with respect to the median skill level of the workforce.

The skill level required to occupy cognitive positions decreased between 1984 and 1991 (table 2 shows that, in 1984, 67% of workers already employed in these positions and 75% of the new entries<sup>5</sup> had a diploma above the median, while in 1991 these percentages attained only 45% and 50%, respectively) and raised again in 1998 and 2005 when 60%-65% of young people hired in cognitive jobs had a diploma above the median. This U-shaped evolution of the skill requirements demanded to fill cognitive positions together with the huge increase of non routine cognitive positions and decrease of routine ones (see figure 1) tends to support the idea that the diffusion of ICT during the 90s (see third column of table 2) favored a progressive substitution of medium-skilled workers in cognitive routine positions by computer capital. Working with the U.S. Dictionary of Occupational Skills, Ingram and Newmann (2006) find similar results: the median “intelligence” and “coordination” levels required for jobs increased since the second half of the eighties after a period of stability. Conversely the requirements for the skills “strength” and “fine motor skill” declined.

<sup>5</sup>To avoid demographical effects we distinguish already employed workers from those that have less than 30 years old and less than a year of seniority at their position.

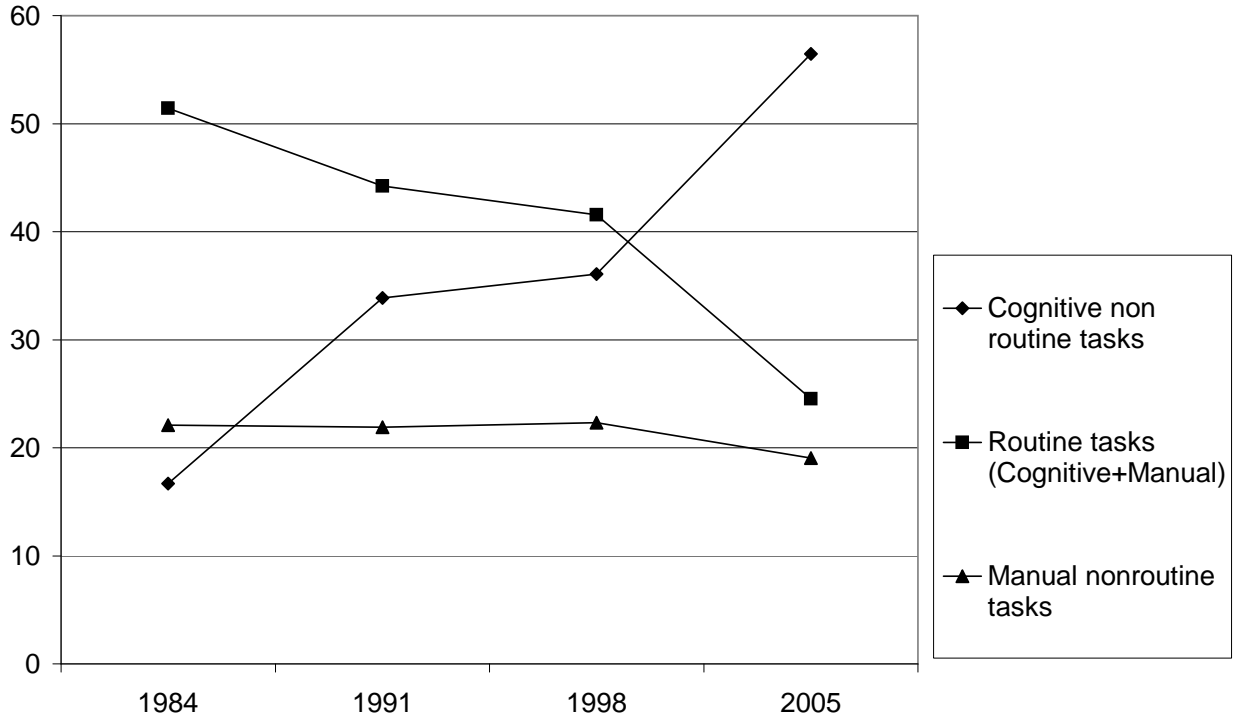


Figure 1: Proportion of labor input in routine and non routine tasks, France 1984-1998.

Furthermore we also find that the proportion of overeducated workers in simple tasks<sup>6</sup> increased from 40% in 1984 to 60-65% in 2005, suggesting that the simple labor market segment is receiving the medium-skilled workers that do not longer qualify for complex jobs.

The previous analysis is completed by a more formal econometric approach (see table 3), where we estimate the probability (probit model) to occupy a cognitive position in 1984, 1991, 1998 and 2005 controlling for age, seniority, gender, diploma, nationality, partial time jobs, firm's size, occupation and economic sector. We focus on the coefficients associated to the number of years of schooling (diploma) and we take as reference the absence of diploma. Because the sample differs from one year to another we cannot make temporal comparisons. Nevertheless, we can determine the relationship between a diploma level and the probability to occupy a cognitive position within a year, as well as the dynamics of the coefficient hierarchy.

Whereas in 1984 people with graduate and postgraduate diplomas had the highest probability to occupy a cognitive position, in 1991 this position corresponds to workers with an undergraduate diploma. From 1998 the situation changes again and people with graduate and postgraduate diploma start being those with the highest probability to fill a complex job. These estimations

<sup>6</sup>We first estimate the mean diploma held by people employed in simple tasks and then compute the proportion of workers having a diploma above this mean.

seem thus to confirm that the minimum skill level found in cognitive positions displays a non monotonous path.

	<b>All cognitive positions</b>			
	1984	1991	1998	2005
BEPC	0.304	0.194	0.204	0.133
CAP - BEP	0.055	0.159	0.125	-0.002
Baccalaureate	0.326	0.354	0.477	0.064
Undergraduate	0.297	0.469	0.569	0.192
Graduate-Postgraduate	0.461	0.334	0.819	0.208
Obs.	5110	6774	7142	5183
$R^2$	0.48	0.59	0.56	0.16

Table 3: Probability of occupying a cognitive position by skill level.

The empirical evidence presented in this section supports the idea that the skill requirements demanded by firms to fill complex vacancies have followed an U-shaped path. The progressive disappearance of cognitive routine tasks, which have been replaced by computer capital, and the emergence of non routine cognitive positions has led firms to augment the skill requirements to occupy complex positions, since the implementation of these tasks requires a wider human capital. The job destruction rates supported by medium qualified workers occupied in cognitive tasks have continuously increased (there is a slight downturn in 2002) whereas those of high-skilled workers have continuously decreased (see figure 2).

## 2.2 Technological change and task composition

In this section we seek to analyze the relationship between the introduction of ICT and the share of labor employed in non routine cognitive positions. According to Autor et al. (2003) computer

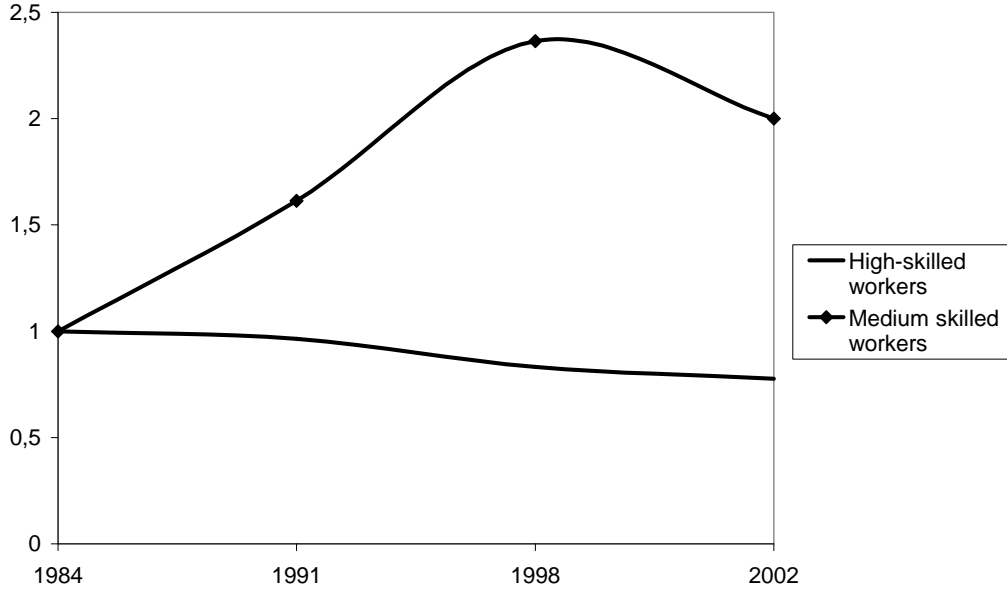


Figure 2: Job destruction rates in cognitive tasks.

capital is a substitute for routine manual and routine cognitive tasks and complementary to non routine cognitive activities (no conclusion on the relationship between ICT and changes in non routine manual task inputs is derived from their theoretical model). Following the same approach as Spitz-Oener (2006), table 4 investigates these substitution and complementary hypothesis for the French case.

Table 4 displays the first difference relationship between workplace computerization and changes in the occupational task requirements. Each column represents a separate ordinary least square (OLS) regression of the annual changes in occupational task measures<sup>7</sup> on the annual changes in computer use. Annual changes are estimated between successive waves, that is, between 1984 and 1991, between 1991 and 1998 and between 1998 and 2005. The regressions are based on the stacked data set<sup>8</sup>.

The results show that occupations that saw greater increase in computerization witnessed significantly larger increases in the non routine task requirements. The theoretical model developed

<sup>7</sup>For each occupation we compute the proportion of workers implementing manual routine tasks, cognitive tasks (non routine+routine tasks) and non routine cognitive tasks. We exclude manual non routine tasks since no prediction of the effect of ICT on these positions is anticipated by the literature.

<sup>8</sup>In every wave of the Complementary Survey on Working Conditions each occupation is characterized by a measure capturing the proportion of workers employed in that occupation and implementing manual tasks and cognitive tasks (routine and non routine in both cases). The data corresponding to each wave is then stacked in a single data set.

in next sections should then interiorize the fact that novel technologies mainly favor the productivity, and thus the demand, of labor input employed in non routine cognitive tasks (these positions are essentially filled by the highest skilled workers in cognitive jobs).

	Manual routine	Cognitive	Non routine cognitive
$\Delta$ Computer use	-0.0038 (0.1780)	0.0289 (0.1651)	0.3216 (0.1807)***
Obs	75	75	75

Standard errors are in parentheses; regressions are weighted by the number of individuals within an occupational group.  
 \* Significant at the 10% level. \*\* Significant at the 5% level. \*\*\* Significant at the 1% level.

Table 4: Technological change and changes in the labor input task composition.

### 3 The model

The objective of this paper is to analyze the transition from the “skill biased technological progress” to the “task biased technological progress”. To this end, we assume that the economy is composed by a continuum of workers individually characterized by a given skill or ability level. We extend Mortensen and Pissarides (1999) by showing that this framework leads to an endogenously segmented labor market between workers having at least the threshold ability level giving access to complex positions, and the rest of the workers which can only occupy simple positions. There is an endogenous job destruction due to idiosyncratic shocks. Firms offering a cognitive job support a set up cost but adoption of new technologies is supposed to improve their productivity. Finally, to capture the positive spillovers induced by novel technologies in the general standard of living, unemployment benefits are indexed to aggregate productivity.

#### 3.1 Assumptions

##### 3.1.1 Worker’s ability and technology of production

We assume an endogenous job destruction framework, where the ability levels  $a(i)$  are drawn from the distribution  $g(a(i))$  over an interval  $[\underline{a}, \bar{a}] = [0, 1]$ . The firm may offer either a complex job, in which the worker implements cognitive tasks, or a simple job, in which the worker implements more manual tasks. A cognitive job is associated to a fixed coefficients technology

requiring one worker with a skill level above a threshold value  $a(\tilde{i})$  to produce  $p \cdot a(i) + \varepsilon$  units of output per period, where  $\varepsilon$  is a random idiosyncratic productivity shock,  $a(i)$  stands for the worker's skill level and  $p$  represents the unitary productivity associated to each ability level (state of technology). The simple job is associated to a fixed coefficients technology requiring one worker to produce  $h + \varepsilon$  units of output per period, where  $\varepsilon$  represents the random idiosyncratic productivity shock and  $h$  the deterministic productivity component. In this type of tasks the worker's ability level does not enhance productivity. The worker does not need any particular training to become productive in a single task, the systematic exposure to it will be enough to learn the task. The differentiated definition of the deterministic productivity component between simple and complex jobs seeks to capture one stylized fact: the IT revolution has particularly favored productivity of workers employed in non routine cognitive positions (see section 2).

### 3.1.2 The matching process

Firms perfectly know the distribution of abilities among workers. Moreover, when opening a vacancy they specify the required ability level to qualify for it (directed search). The vacancy may then be filled and start producing or remain empty and continue searching. Any job that is not producing or searching is destroyed. In contrast, a job is created when a firm with a vacant job and a worker meet and both decide to start producing (it is mutually profitable to produce).

We distinguish between two large categories of workers: those having at least an ability level  $a(\tilde{i})$  giving access to cognitive positions and those having a qualification below  $a(\tilde{i})$  who can only apply to simple positions. In spite of having the possibility to occupy a complex vacancy, it may be in the interest of a worker with an ability level above  $a(\tilde{i})$  to search in the simple segment if her probability to find a complex job is too low. Let's call  $a(\hat{i}) > a(\tilde{i})$  the threshold skill level below which it is in the interest of a worker to search a simple job.

The number of contacts per period in the simple segment ( $M_t^S$ ) is represented by the following linear homogeneous matching function  $M_t^S = m(v^S, \sum_{j=1}^{\hat{i}} u^j)$ . The labor market tightness in the simple segment is then given by the ratio between the number of simple vacancies open in the economy ( $v^S$ ) and the total number of unemployed having an ability level below  $a(\hat{i})$  (unemployed workers that can apply to simple vacancies,  $\sum_{j=1}^{\hat{i}} u^j$ ):  $\theta^S = \frac{v^S}{\sum_{j=1}^{\hat{i}} u^j}$ . In the simple segment, workers with divergent ability levels compete for a given type of job. The larger the number of people with different skill levels looking for a simple job, the lower will be the labor market tension ( $\theta^S$ ) of this segment and the more intense job competition. The probability

of filling a simple vacancy equals  $q(\theta^S) = M_t^S/v^S$  and the probability to find a simple job is represented by  $p(\theta^S) = M_t^S/\sum_{j=1}^{\hat{i}} w^j = \theta^S q(\theta^S)$ . This probability falls with the number of job seekers in the simple segment.

For workers with a skill level above the firm's threshold value giving access to cognitive positions ( $a(\tilde{i})$ ), we consider an infinitely segmented labor market in which for each ability level the observed labor market tightness equals  $\theta_i^M = v_i^M/u_i$ , where  $v_i^M$  stands for the number of complex vacancies directed to a skill level  $a(i)$  and  $u_i$  represents the number of unemployed workers with an ability level  $a(i)$ . The number of contacts per period ( $M_{it}^M$ ) is given by  $M_{it}^M = m(v_i^M, u_i)$ . The probability to fill a vacancy requiring a skill level  $a(i)$  equals  $q(\theta_i^M) = M_{it}^M/v_i^M$  and the probability that a worker with ability  $a(i)$  finds a job is  $p(\theta_i^M) = M_{it}^M/u_i = \theta_i^M q(\theta_i^M)$ . A worker with an ability level  $a(i)$  only looks for a job in the ability segment  $a(i)$  since she does not qualify for any job above this ability level and it is not in her interest to apply for a position in a lower ability segment since the probability to find a job decreases.

### 3.1.3 The job productivity shocks

The values of the random idiosyncratic productivity parameter,  $\varepsilon$  are drawn from the distribution  $\Phi$  over the interval  $[\underline{\varepsilon}, \bar{\varepsilon}]$ . The process that changes this idiosyncratic term is the same in both types of jobs and it follows a Poisson distribution with arrival rate  $\lambda \in [0, 1]$ . Therefore, every period there exists a probability  $\lambda$  that the economy is hit by a shock such that a new value of  $\varepsilon$  has to be drawn from  $\Phi$ . Because search and hiring activities are costly, the new productivity level arising after the shock may indeed be too low to compensate either party for their efforts. The productivity level below which it is not in the interest of the firm and the worker to pursue the contact (the surplus associated to the match becomes zero) is called reservation productivity and it will be denoted  $\varepsilon_i^M$  for the complex job and  $\varepsilon^S$  for the simple job.

### 3.1.4 The set up cost

The IT revolution has fostered the emergence of cognitive positions where the worker is required to use computer capital. The first firms introducing these jobs had to support important set up costs. However, as novel technologies got diffused across the economy and complex jobs became increasingly abundant, these set up costs decreased thanks to positive spillovers: the follower firms do not make the same mistakes as the leaders made, so we can assume that the set up

costs associated to the creation of complex positions fall as their number increases. To formalize this idea, we simply define the following process:

$$K(p) = e^{-\gamma(p-p_0)} \quad (1)$$

where  $\gamma$  represents the speed of adjustment,  $p$  is the actual state of technology (productivity of complex positions) and  $p_0$  stands for the final or potential technology level. Notice that initially  $p < p_0$  and at the end of the catch up  $p = p_0$  implying that  $K(p) = 1$ .

Cognitive positions are then offered only to those workers having an ability level above a particular threshold,  $a(\tilde{i})$ , guaranteing the equality between the total creation cost and the expected value of a filled job. The rest of the workers receives simple jobs offers.

## 3.2 Agent Behaviors

An open vacancy can remain empty and searching or be filled and start producing. The associated asset value to each of these situations is represented by  $V^M(a(i))$  (resp.  $V^S$ ) when a complex (resp. simple) vacancy is empty, and by  $J^M(a(i), \varepsilon)$  (resp.  $J^S(\varepsilon)$ ) when the complex (resp. simple) vacancy is filled. In the same way, the value to the worker in a cognitive (resp. simple) job is denoted as  $W^M(a(i), \varepsilon)$  (resp.  $W^S(\varepsilon)$ ). Finally, the average expected return on the worker's human capital when looking for a job is represented by  $U^M(a(i))$  (resp.  $U^S$ ) when the worker's skill level is above (resp. below) the threshold value  $a(\tilde{i})$ .

### 3.2.1 The firms

When the firm opens a vacancy it supports a cost  $c$  per unit of time (these costs are usually considered as advertising and recruitment costs), whatever the skill level required to fill the vacancy. When the vacancy is filled, if the created position is complex, the firm supports a first period set up cost. There is a probability  $1 - q(\theta_i^M)$  and  $1 - q(\theta^S)$  that the complex and simple vacancies remain, respectively, empty next period. On the opposite, there is a probability  $q(\theta_i^M)$  and  $q(\theta^S)$  that the complex and simple vacancies get filled. We assume that the first period idiosyncratic productivity in both types of jobs is at its maximum level,  $\bar{\varepsilon}$ . The asset value associated to a searching vacancy is then:

$$V^M(a(i)) = -c + \beta (1 - q(\theta_i^M)) V^M(a(i)) + \beta q(\theta_i^M) (J^M(a(i), \bar{\varepsilon}) - K(p)) , \quad (2)$$

$$V^S = -c + \beta (1 - q(\theta^S)) V^S + \beta q(\theta^S) J^S(\bar{\varepsilon}) . \quad (3)$$



where  $\beta$  is the discount factor.

When the vacancy is filled and actively producing, there is a probability  $\lambda$  that the job is hit by a shock, so that a new value of  $\varepsilon$  is drawn from the distribution  $\Phi$ . From the second period of the match, the asset values associated to cognitive and simple jobs are respectively defined as<sup>9</sup>:

$$J^M(a(i), \varepsilon) = p \cdot a(i) + \varepsilon - w^M(\varepsilon, a(i)) + \beta (1 - \lambda) \text{Max}[J^M(a(i), \varepsilon), V^M(a(i))] + \beta \lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \text{Max}[J^M(a(i), x), V^M(a(i))] d\Phi(x), \quad (4)$$

$$J^S(\varepsilon) = h + \varepsilon - w^S(\varepsilon) + \beta (1 - \lambda) \text{Max}[J^S(\varepsilon), V^S] + \beta \lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \text{Max}[J^S(x), V^S] d\Phi(x), \quad (5)$$

where  $w^M(\varepsilon, a(i))$  and  $w^S(\varepsilon)$  represent, respectively, the wages paid to a worker in a multitask (complex) job and in a specialized (simple) job. The firm opens vacancies until all rents are exhausted, that is:

$$\frac{c}{\beta q(\theta_i^M)} = (J^M(a(i), \bar{\varepsilon}) - K(p)), \quad (6)$$

$$\frac{c}{\beta q(\theta^S)} = J^S(\bar{\varepsilon}). \quad (7)$$

### 3.2.2 The workers

An unemployed worker receives a flow of earnings  $w_i^u$  including unemployment benefits, leisure, domestic productivity, etc. These earnings represent the worker's outside option or reservation wage, and we assume them to be a function of the economy's aggregate productivity. In the aim of simplicity and realism we will assume that the unemployment benefit earned by someone in the complex segment remains above the unemployment benefit obtained by someone in the simple segment,  $w_M^u > w_S^u$ .

A job seeker with an ability  $a(i) > a(\tilde{i})$  comes in contact with a complex vacant slot at rate  $\theta_i^M q(\theta_i^M)$  while a job seeker looking for a simple job comes in contact with a vacancy at rate  $\theta^S q(\theta^S)$ . The asset value of unemployment to both types workers is respectively given by:

$$U^M(a(i)) = w_M^u + \beta (1 - \theta_i^M q(\theta_i^M)) U^M(a(i)) + \beta \theta_i^M q(\theta_i^M) W^M(a(i), \bar{\varepsilon}) \quad (8)$$

$$U^S = w_S^u + \beta (1 - \theta^S q(\theta^S)) U^S + \beta \theta^S q(\theta^S) W^S(\bar{\varepsilon}). \quad (9)$$

---

<sup>9</sup>The asset values associated to the starting period of the match simply differ from the continuing asset values on the fact that the the idiosyncratic productivity is assumed to be at its maximum level.

The asset value of unemployment of a worker searching in the simple segment is independent of her ability because his job opportunities and unemployment benefits do not depend on it.

Even if a worker has the required qualification to occupy a complex job, she may decide to search in the simple segment if her asset value of unemployment is larger. All workers having an ability level below a critical  $a(\hat{i})$  for which  $U^M(a(\hat{i})) = U^S = U$ , will search in the simple segment even if they have the required skills to apply for complex jobs.

A cognitive job with productivity  $p \cdot a(i) + \varepsilon$  pays a wage  $w^M(a(i), \varepsilon)$  to the worker, while a simple job with productivity  $h + \varepsilon$  pays  $w^S$ . Both types of jobs are hit by a shock with probability  $\lambda$ . The present value of a cognitive and a simple job to the worker solve<sup>10</sup>:

$$\begin{aligned}
W^M(a(i), \varepsilon) &= w^M(a(i), \varepsilon) + \beta (1 - \lambda) \text{Max}[W^M(a(i), \varepsilon), U^M(a(i))] + \\
&\quad + \beta \lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \text{Max}[W^M(a(i), x), U^M(a(i))] d\Phi(x) \\
W^S(\varepsilon) &= w^S(\varepsilon) + \beta (1 - \lambda) \text{Max}[W^S(\varepsilon), U^S] + \\
&\quad + \beta \lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \text{Max}[W^S(x), U^S] d\Phi(x). \tag{11}
\end{aligned}$$

### 3.2.3 The wage bargaining process

Since search and hiring activities are costly, when a match is formed a joint surplus is generated. At the beginning of every period the firm and the employee renegotiate wages through a Nash bargaining process, that splits the joint surplus into fixed proportions at all times (see appendix B for further details). Denoting as  $\eta \in (0, 1)$  the bargaining power of workers, we have the following wages<sup>11</sup> :

$$w^M(a(i), \varepsilon) = (1 - \eta) w_M^u + \eta(p \cdot a(i) + \varepsilon + c\theta_i^M), \tag{12}$$

$$w^S(\varepsilon) = (1 - \eta) w_M^u + \eta(h + \varepsilon + c\theta^S). \tag{13}$$

<sup>10</sup>For the first period of the match the idiosyncratic productivity component is set to  $\bar{\varepsilon}$ .

<sup>11</sup>As explained in appendix B, during the first period of the match the idiosyncratic productivity is assumed to be at  $\bar{\varepsilon}$  for both types of jobs. Furthermore, in cognitive positions, the firm shares during this first period the set up cost with workers. As Lindquist (2002) demonstrates, this bitemporal specification of the wage negotiation in the complex segment is equivalent to just assuming a unique wage bargaining negotiation without set up costs.

## 4 The steady state

### 4.1 The unemployment benefit

We introduce the role of labor market institutions by assuming that unemployment benefits are indexed to general productivity. As remarked in Pissarides (2000), indexing the unemployment benefit to the average wage creates complications in a model like ours where the equilibrium is characterized by a conditional wage distribution and not by a unique wage rate. In these cases a convenient shortcut that does not sacrifice important generality is to define benefits in terms of the general productivity parameter  $p$ , which is unique and exogenous. Whether indexed to the average wage or to the productivity parameter, the intuitive idea behind this formalization of the unemployment benefit is that the European unemployment system is redistributive, therefore improvements in the general standards of living are reflected on the unemployment benefit.

For high productivity workers (unemployed people in the complex segment) the unemployment benefit is completely indexed to their productivity level:  $w_M^u = \delta_M \cdot p$  with  $\delta_M$  being a positive constant smaller than 1. For low productivity workers (simple segment), the situation is somewhat different since labor market institutions guarantee a minimum of subsistence so that  $w_S^u = b + \delta_S \cdot p$  where  $b$  is the fixed component representing a subsistence minimum, and  $\delta_S \cdot p$  is the indexed component, with  $\delta_S$  being a positive constant smaller than  $\delta_M$ .

### 4.2 Job creation and job destruction rules

Every period there is a probability  $\lambda$  that a shock arrives. Once the new value of  $\varepsilon$  is drawn from the distribution  $\Phi$ , the continuity of the match depends on the positivity of the surplus. As far as the joint surplus (the one obtained by the firm plus the one of the worker) is positive, the job goes on. If the joint surplus becomes negative, the match breaks down. For each type of job there exists thus a critical productivity level,  $\varepsilon_i^M$  and  $\varepsilon_i^S$ , such that  $S^M(a(i), \varepsilon_i^M) = 0$  and  $S^S(\varepsilon_i^S) = 0$ . Below these reservation productivity levels the surplus is negative and it is not profitable to pursue the job (remark that in the first period of the match, the idiosyncratic productivity is set to its maximum value, such that all matches pursue at least one more period).

Integrating by parts yields the following expressions for the cognitive and simple job destruction

rules (see appendix B for the derivation of the threshold values  $\varepsilon_i^M$  and  $\varepsilon^S$ ):

$$\frac{\eta}{1-\eta} c \theta_i^M = p \cdot (a(i) - \delta_M) + \varepsilon_i^M + \frac{\beta \lambda}{1 - \beta(1 - \lambda)} \int_{\varepsilon_i^M}^{\bar{\varepsilon}} (1 - \Phi(x)) dx, \quad (14)$$

$$\frac{\eta}{1-\eta} c \theta^S = h - (\delta_S \cdot p + b) + \varepsilon^S + \frac{\beta \lambda}{1 - \beta(1 - \lambda)} \int_{\varepsilon^S}^{\bar{\varepsilon}} (1 - \Phi(x)) dx. \quad (15)$$

At the steady state the firms open vacancies until no more benefit can be obtained, that is, all rents are exhausted and the free entry condition applies:  $V^M(a(i)) = 0$  and  $V^S = 0$ . From equations (2), (3), (4), (5), the wage equations (12) and (13) as well as the critical productivity levels provided by expressions (14) and (15), we derive the following job creation rules:

$$\frac{c}{\beta q(\theta_i^M)} = (1 - \eta) \left[ \frac{(\bar{\varepsilon} - \varepsilon_i^M)}{1 - \beta(1 - \lambda)} - K(p) \right], \quad (16)$$

$$\frac{c}{\beta q(\theta^S)} = \frac{(1 - \eta)(\bar{\varepsilon} - \varepsilon^S)}{1 - \beta(1 - \lambda)}. \quad (17)$$

where  $K(p) = e^{-\gamma(p-p_0)}$ .

### 4.3 The equilibrium labor market tightness and reservation productivity

#### 4.3.1 Simple jobs

For simple jobs (occupied by workers with an ability level smaller than  $a(\hat{i})$ ), we find the traditional job creation-job destruction theoretical framework introduced by Mortensen and Pissarides (1994). As figure 3 shows, in this setup, the job creation curve (equation (17)) is strictly decreasing in the space  $[\varepsilon, \theta^S]$  and the job destruction curve (equation (15)) strictly increasing, guaranteeing the existence of a unique equilibrium point  $[\varepsilon^{S*}, \theta^{S*}]$  (see appendix C for proofs).

#### 4.3.2 Complex jobs

In the complex segment the equilibrium is also characterized by the job creation and destruction curves. However, when dealing with cognitive positions we must distinguish between three variables of interest: the reservation productivity ( $\varepsilon_i^M$ ), the labor market tightness ( $\theta_i^M$ ) and the ability level corresponding to the considered labor market segment ( $a(i)$ ). We thus represent in this section the job creation and the job destruction curves either in the  $[\theta_i^M, \varepsilon_i^M]$  space for a given  $a(i)$ , or in the  $[a(i), \varepsilon_i^M]$  space for a given  $\theta_i^M$  ( $\theta_i^M = 0$ ) in section 4.4.

For any  $a(i) > a(\tilde{i})$ , the equilibrium labor market tightness and reservation productivity of the ability segment is determined by the intersection between the job creation (equation (16)) and

the job destruction (equation (14)) curves. While the former curve is negatively sloped, the last one has a positive slope (see appendix C for proofs), guaranteeing the existence of a unique equilibrium (see figure 3).

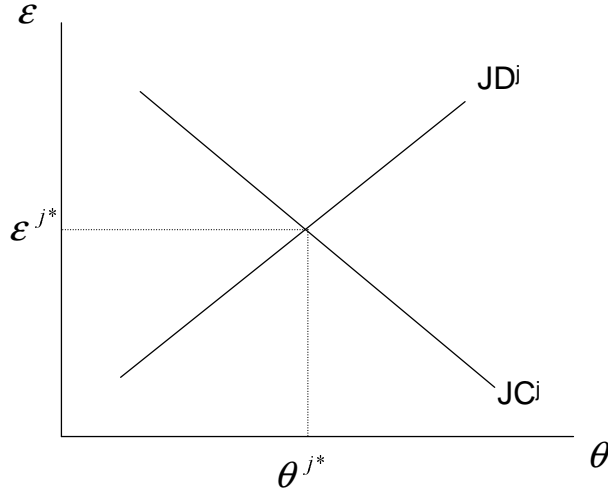


Figure 3: Equilibrium situation in the  $j$  segment, where  $j$  stands for the simple segment or for any of the complex segments  $a(i) > a(\tilde{i})$ .

#### 4.4 The endogenous segmentation of the labor market

##### 4.4.1 The firm's critical ability level for complex jobs

Because firms offering a cognitive position must support a set up cost equal to  $K(p)$  during the first period of the contact, they will direct their open vacancies to workers having the ability level required to compensate this cost. Nevertheless, it is not optimal for the firms to direct all the job offers towards the most highly qualified workers because congestion effects would arise in this ability segment and vacancies would tend to remain empty forever. The minimum ability level required to exactly compensate the set up cost of opening a cognitive position is given by  $a(\tilde{i})$ . At this point, the number of vacancies converges to zero (implying that  $\theta_i^M$  tends to zero and the probability to fill a vacancy tends to infinity), leading to the following free entry condition:

$$\frac{\bar{\varepsilon} - \varepsilon_i^M}{(1 - \beta(1 - \lambda))} = K(p) = e^{-\gamma(p-p_0)}. \quad (18)$$

For small values of  $p$ , that is, for a low degree of penetration of novel technologies, the value of the set up cost ( $K(p)$ ) is high since complex positions are not abundant. This cost will need to be compensated by a large expected value of the filled position which requires  $\varepsilon_i^M$  to be low (a reduced value of the critical productivity level ensures a longer duration of the match).

The firm must then determine the ability level,  $a_i = a(\tilde{i})$ , supporting this reservation productivity. To this end, we set  $\theta(\tilde{i})$  to zero in the job destruction rule (equation (14)):

$$\varepsilon_i^M = p \cdot (\delta_M - a(\tilde{i})) - \frac{\beta \lambda}{1 - \beta(1 - \lambda)} \int_{\varepsilon_i^M}^{\bar{\varepsilon}} (1 - \Phi(x)) dx \quad (19)$$

High ability levels allow to compensate low idiosyncratic productivity shocks, since the high deterministic productivity component overcomes the reduced idiosyncratic component. When firms direct their vacancies towards low ability levels, their expected lifetime durations are shorter (the idiosyncratic reservation productivity must increase to compensate the low deterministic component). Finally, remark that the lowest ability hired on a cognitive job is such that its induced expected lifetime duration allows to exactly recoup the set up costs. Combining equations (18) and (19) yields the equilibrium value of the threshold ability level required by firms in complex jobs:

$$a(\tilde{i}) = \frac{1}{p} [p\delta_M - (\bar{\varepsilon} - K(p)(1 - \beta(1 - \lambda))) - \frac{\beta \lambda}{1 - \beta(1 - \lambda)} \int_{\varepsilon_i^M}^{\bar{\varepsilon}} (1 - \Phi(x)) dx] \quad (20)$$

We represent equations (18) and (19) in the  $[a(i), \varepsilon_i^M]$  space. While the job creation simply corresponds to a straight horizontal line in this space, the job destruction is negatively sloped<sup>12</sup>. The intersection between both of them determines the critical ability level required by firms in cognitive positions (see figure 4). For an initial low value of  $p$  we expect  $\varepsilon_i^M$  to be negative. Because the set up costs are large, firms are more demanding in terms of the minimum  $a(\tilde{i})$  required to fill a complex job, implying that, initially, the deterministic productivity component is high. This allows to support a small idiosyncratic component.

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<sup>12</sup>Differentiating with respect to  $\varepsilon_i^M$  leads to:

$$1 - \frac{\beta \lambda}{1 - \beta(1 - \lambda)} (1 - \Phi(\varepsilon_i^M)) = -p \cdot \frac{\partial a(\tilde{i})}{\partial \varepsilon_i^M} \quad (21)$$

Because  $0 < \frac{\beta \lambda}{1 - \beta(1 - \lambda)} (1 - \Phi(\varepsilon_i^M)) < 1$ , the left hand side of the previous equation is positive implying that  $\frac{\partial \varepsilon_i^M}{\partial a(\tilde{i})} < 0$ . When the critical ability level increases the minimum productivity required to pursue the job falls.

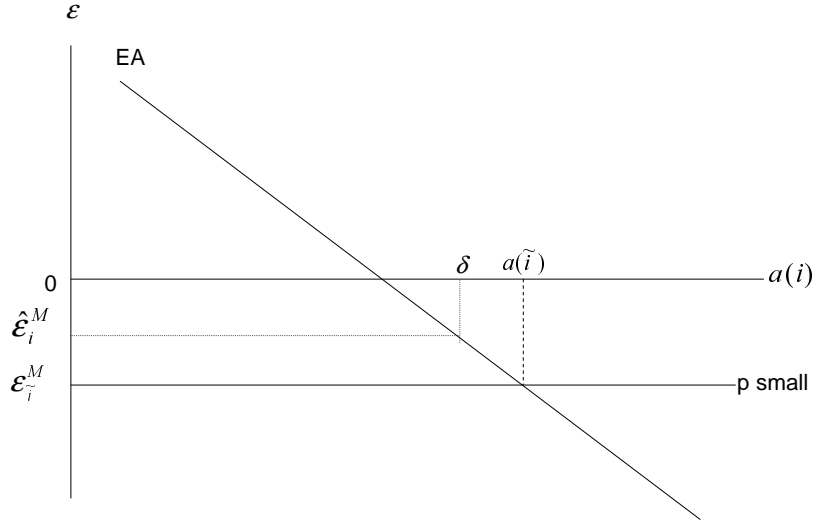


Figure 4: Equilibrium ability and reservation productivity in multitask jobs.

#### 4.4.2 The worker's critical ability level for complex jobs

On the other hand, even if someone has an ability level above  $a(\tilde{i})$ , it might be in her interest to search in the simple segment if the number of cognitive vacancies open in her ability slot is too low. A worker with an ability level  $a(i) > a(\tilde{i})$  decides to search in the simple side of the labor market if her asset value of unemployment when remaining in the cognitive segment is below her asset value of unemployment when looking for a manual job. The critical ability level  $a(\hat{i})$  below which someone having the possibility to occupy a complex position decides to search rather for a simple job is determined by the equality between the asset values of unemployment:

$$\begin{aligned}
 U^M(\hat{i}) &= U^S \Rightarrow U^M(\hat{i}) - U^S = 0 \\
 \theta_{\hat{i}}^M &= \theta^S + \frac{\beta(1-\eta)}{c\eta}(w_S^u - w_M^u)
 \end{aligned} \tag{22}$$

While being qualified to fill a cognitive position, all workers having a skill level between  $[a(\tilde{i}), a(\hat{i})]$  prefer to search in the simple segment since they have a higher probability to find a job and they do not loose in terms of unemployment benefits<sup>13</sup>.

Furthermore, because  $\theta_{\tilde{i}}^M = 0$ , as far as  $\theta^S + \frac{\beta(1-\eta)}{c\eta}(w_S^u - w_M^u) > 0$ ,  $a(\hat{i})$  will necessarily be strictly larger than  $a(\tilde{i})$ . Remark that in the absence of simple vacancies ( $\theta^S = 0$ ) and under the assumption that  $w_S^u < w_M^u$ , no worker having an ability level above  $a(\tilde{i})$  will look in the simple

<sup>13</sup>In their first period of employment, wages of these workers should be larger than those of low-skilled since their outside option is larger ( $w_M^u > w_S^u$ ). However, from the second period of employment their outside option equals  $w_S^u$ , and their wages will not longer differ from those of low-skilled. The firm offers thus directly  $w^S$  to high-skilled workers employed in simple positions (see appendix B for details)

segment. Therefore we distinguish between two regimes:

- For  $\theta^S + \frac{\beta(1-\eta)}{c\eta}(w_S^u - w_M^u) > 0$ , the unemployment benefits perceived in the complex segment do not manage to compensate the weak probability to find a cognitive job. Workers prefer thus to search in the simple segment of the labor market even if they have the required ability to occupy a complex position. In this equilibrium with workers' mobility the segmentation of the labor market is determined by  $a(\hat{i})$ .
- For  $\theta^S + \frac{\beta(1-\eta)}{c\eta}(w_S^u - w_M^u) \leq 0$ , unemployment benefits compensate the low probability to find a cognitive job, and all workers with an ability level above  $a(\tilde{i})$  remain searching in the complex segment. In this equilibrium with no workers' mobility the segmentation is given by  $a(\tilde{i})$ .

Firms will not direct all the job offers towards the most highly qualified segments, so as to avoid congestion effects, but no job offers will neither be directed to those ability segments for which there are no job seekers, that is, there will be no posted vacancies within the interval  $[a(\tilde{i}), a(\hat{i})]$  if we are in the first regime.

## 5 The effects of a biased technological shock

We develop a comparative static exercise seeking to analyze the effects of a biased technological shock on the critical ability level required in cognitive positions, on the labor flows of different skill categories, on job creation and destruction as well as on job competition. We consider an initial situation characterized by a very low  $p$  (low degree of penetration of ICT) and assume a progressive increase in  $p$  towards  $p_0$ . To be illustrative, we impose an initial situation where  $p$  is low ( $K$  high) and there are no cognitive positions in the economy, *i.e.*  $a(\tilde{i}) = \overline{a(i)} = 1$ . As the economy starts its technological development,  $p$  raises, reducing the gap between  $p$  and  $p_0$  and fostering the appearance of complex positions, whose productivity is enhanced. The diffusion of complex jobs promotes a gradual reduction in the set up costs supported by firms, *i.e.* fall in  $K(p) = e^{-\gamma(p-p_0)}$ .

### 5.1 Simple jobs

The equilibrium in the simple segment is characterized by two equations, the job destruction and job creation curves, respectively given by (15) and (17). A variation in  $p$  only affects the job



destruction curve<sup>14</sup>, which shifts up (see figure 10 in appendix D), determining a new equilibrium where the reservation productivity required to pursue the match is higher and the labor market tightness lower.

Even if the productivity of workers employed in simple jobs is not affected by the technological shock, their reservation wage increases following the upturn in  $p$  ( $w_S^u$  is partly indexed to  $p$ ) fostering a reduction in the number of simple vacancies. The labor market tension decreases and the average waiting time for a firm to fill a simple vacancy ( $\frac{1}{q(\theta^S)}$ ) too. Because it takes less time to fill a vacancy (it is also less costly to open one) the firm becomes more demanding concerning the productivity level,  $\varepsilon^S$ , required to pursue the match (the firm destroys more easily the match since it can also fill it easily).

### Proposition

*A biased technological change exclusively favoring the productivity of cognitive positions but increasing the general standards of living, decreases the labor market tightness ( $\theta^S$ ) and increases the reservation productivity ( $\varepsilon^S$ ) in the simple segment. Unambiguously, the number of simple jobs in the economy decreases.*

## 5.2 Complex jobs

Determining the effects of a biased technological shock on the complex segment becomes a slightly more complicated issue. Our analysis covers two stages: we first analyze the impact of a biased technological shock on the labor market equilibrium (reservation productivity and labor market tension) of a particular ability slot. In a second stage, we study the effects of the technological change on the endogenous segmentation of the labor market. More precisely, we analyze the impact on the minimum ability level required to qualify to complex positions. By means of this two-steps analysis we manage to provide a complete picture of the equilibrium in the complex segment.

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<sup>14</sup>

$$\frac{\partial p}{\partial \varepsilon^S} = \frac{\delta[1 - \beta(1 - \lambda\Phi(\varepsilon))]}{1 - \beta(1 - \lambda)} > 0 \quad (23)$$

### 5.2.1 How do ICT shift the labor market equilibrium in each ability slot?

For a given  $a(i) > a(\tilde{i})$ , both the job creation and the job destruction curves are affected by a biased technological change. The job creation is affected via the set up cost and the probability of filling a vacancy, while the job destruction curve is influenced via the improvement in the workers' productivity and the rise in the outside option.

We start with the job creation curve, whose variation in case of shock is given by:

$$d\theta_i^M = Z \left[ \frac{-d\varepsilon_i^M}{1 - \beta(1 - \lambda)} + \gamma K(p) dp \right] \quad \text{where} \quad Z = -\frac{\beta(1 - \eta) q(\theta_i^M)}{c \frac{q'(\theta_i^M)}{q(\theta_i^M)}} > 0 \quad \text{since} \quad q'(\theta_i^M) < 0 \quad (24)$$

An increase in  $p$  positively affects the labor market tightness, while the relationship between the reservation productivity and the labor market tightness continues to be negative (the job creation curve is negatively sloped in the  $(\theta_i^M, \varepsilon_i^M)$  space). For a given  $\varepsilon_i^M$  the labor market tightness raises if  $p$  increases (the job creation curve shifts right). The diffusion of ICT is associated to a progressive reduction of the set up cost supported by firms offering cognitive positions. The opening of complex vacancies is thus stimulated.

The variation of the job destruction curve in case of shock is given by:

$$d\varepsilon_i^M \left( 1 - \frac{\beta \lambda}{1 - \beta(1 - \lambda)} (1 - \Phi(\varepsilon_i^M)) \right) = \frac{\eta}{1 - \eta} c d\theta_i^M + dp \cdot (\delta_M - a(i)) - p da(i), \quad (25)$$

If  $\theta_i^M$  is constant, there exists an ability level  $a(i) = \delta_M$  such that the term  $(\delta_M - a(i)) \cdot p$  cancels and the job destruction curve remains unaffected by the biased technological shock. On the other hand, workers having a high ability level will benefit from a more important increase in their productivity than in their wage ( $\delta_M < a(i)$  then  $p\delta_M < pa(i)$ ). The reservation productivity level required to pursue these matches falls (the job destruction curve shifts right), improving job stability for high-qualified workers. Finally, workers having a low ability level ( $\delta_M > a(i)$ ) profit from a larger increase in their wages than in their deterministic productivity ( $p\delta_M > pa(i)$ ), which shifts the job destruction curve upward and fosters a rise in the reservation productivity required to pursue the match.

Combining both, the movement of the job creation curve and the one of the job destruction curve we may distinguish between three possible situations. If  $a(i)$  equals  $\delta_M$  or is nearby, the new equilibrium will be characterized by a higher reservation productivity and labor market

tension (see case A<sup>15</sup> figure 11 in appendix D). For high ability levels, productivity gains ( $pa(i)$ ) in case of technological shock largely compensate the rise in wages ( $p\delta_M$ ), leading to a new equilibrium where the number of vacancies increases (higher labor market tension) and the reservation productivity falls (case B figure 11). Finally, for a “sufficiently small”<sup>16</sup> ability level, the job destruction curve moves upward fostering a fall in the labor market tension and a rise in the critical productivity level required to pursue the match (case C figure 11). However, this shift is downward bounded by  $\theta_i^M = \theta^S + \frac{\beta(1-\eta)}{c\eta}(w_S^u - w_M^u)$  (vertical line  $B$  in figure 11), since all individuals in an ability slot having a labor market tension below this bound will prefer to search in the simple segment. The complex segment disappears thus from this threshold ability level  $a(\hat{i})$ <sup>17</sup>.

### Proposition

*In the complex segment, the biased technological shock increases (decreases) the reservation productivity and decreases (increases) the labor market tension for those workers having very low (very high) ability levels.*

#### 5.2.2 How do ICT affect the worker’s selection problem?

Any firm offering a cognitive position must support an initial set up cost equal to  $K(p)$ . The firm offers thus this type of positions only to workers having at least a minimum ability level,  $a(\tilde{i})$ , compensating the initial set up costs. At this critical ability level the labor market tightness

<sup>15</sup>In an extreme case we might find a situation where the shift of the job destruction curve is such that  $\varepsilon_i^M$  ( $\theta_i^M$ ) remains unaffected and  $\theta_i^M$  ( $\varepsilon_i^M$ ) increases.

<sup>16</sup>More formally, replacing  $d\theta_i^M = Z\gamma K dp - \frac{Z}{1-\beta(1-\lambda)}$  in equation (25) we can determine how the final equilibrium in the considered labor market segment will be affected by the technological shock:

$$d\varepsilon_i^M \left[ 1 - \frac{\beta\lambda}{1-\beta(1-\lambda)}(1 - \Phi(\varepsilon_i^M)) \right] + \frac{c\eta}{1-\eta} \frac{Z}{1-\beta(1-\lambda)} = dp \left( \frac{\eta}{1-\eta} cZ\gamma K(p) + \delta_M - a(i) \right) - pda(i),$$

When the productivity gains derived from the increase in  $p$  (*i.e.*  $pa(i)$ ), are exactly compensated by the rise in wages and vacancy costs (*i.e.*  $\frac{\eta}{1-\eta} cZ\gamma K(p) + \delta_M = a(i)$ ) changes in  $p$  do not affect the associated reservation productivity level (extreme situation of case A). For workers having high ability levels overcoming the upturn in wages and in intertemporal vacancy costs (*i.e.*  $\frac{\eta}{1-\eta} cZ\gamma K(p) + \delta_M < a(i)$ ), job stability is improved, since the reservation productivity level,  $\varepsilon_i^M$ , falls (case B). If productivity gains fostered by the technological change are too small to compensate for the increase in wages and in the intertemporal cost of opening a vacancy (*i.e.*  $\frac{\eta}{1-\eta} cZ\gamma K(p) + \delta_M > a(i)$ ), the reservation productivity raises (case C).

<sup>17</sup>Remark that if  $\delta_M < a(\hat{i})$  all workers in the complex segment will benefit from a larger increase in their productivity than in their wages. In contrast, for  $\delta_M > a(\hat{i})$  the three previously described situations may arise.

equals zero. All workers included in the interval  $[a(\tilde{i}), a(\hat{i})]$  can theoretically apply to a cognitive position, however since the number of vacancies offered in their ability slot is too low, it may be in their interest to search rather in the simple segment, if their probability to find a job corrected by the difference in the unemployment benefits is larger. At  $a(\hat{i})$  the worker is indifferent between searching in the simple or the complex segment. We analyze in this section the effects of a progressive increase in  $p$  on the size of each labor market segment (minimum ability level found in complex jobs).

### Without mobility

When unemployment benefits manage to compensate the low probability to find a complex job, all workers with an ability  $a(i) > a(\tilde{i})$  search for a cognitive position and no mobility is observed. Even if they support high unemployment rates, it is in the interest of these workers to remain searching in the cognitive segment because unemployment benefits are high. In this context  $a(\hat{i})$  equals  $a(\tilde{i})$  and we have  $\theta_i^M = \theta^S + \frac{\beta(1-\eta)}{c\eta}(w_S^u - w_M^u) \leq 0$ .

To determine the impact of a biased technological shock on the critical ability level  $a(\hat{i}) = a(\tilde{i})$ , we work with the job creation and the job destruction curves defined for  $\theta(i) = 0$  (equations (18) and (19)). In case of biased technological shock, the job creation curve will shift upwards, since:

$$\frac{\partial \varepsilon_i^M}{\partial p} = \gamma e^{-\gamma(p-p_0)}(1 - \beta(1 - \lambda)) > 0 \quad (26)$$

The job destruction curve rotates rightward:

$$d\varepsilon_i^M \left(1 - \frac{\beta\lambda}{1 - \beta(1 - \lambda)}(1 - \Phi(\varepsilon_i^M))\right) = dp(\delta_M - a(i)) - pda(i). \quad (27)$$

More precisely, the rotation point corresponds to the ability level whose associated reservation productivity remains unaffected by the variation in  $p$ . This ability level is thus given by  $\delta_M = \widehat{a(i)}$ .

In a context where  $p$  is progressively increasing (IT revolution), the effect on the final critical ability level required in cognitive positions, results from the combination of the upward shift of the creation curve and the rightward rotation of the destruction curve. Totally differentiating equation (20) leads to:

$$\frac{da(\tilde{i})}{dp} = \frac{\delta - [a(\tilde{i}) + K(p)\gamma\{(1 - \beta(1 - \lambda)) - \frac{\beta\lambda}{1 - \beta(1 - \lambda)}(1 - \Phi(\varepsilon_i))\}]}{p}.$$

If productivity gains ( $pa(i)$ ) together with the actualized reduction<sup>18</sup> in the set up cost manage to overcome the rise in the reservation wage (given by  $\delta_M$ ), then the skill requirement to occupy a complex position falls. This implies that a larger share of the labor force has access to cognitive positions. Conversely, when the difference between the rise in wages, the productivity gains and the effective variation in the set up costs is positive, firms increase the skill level required to fill complex vacancies. Because labor input has become relatively more expensive, firms require a higher skill level to promote productivity and compensate for the higher wages.

For reasonable parameter values, the initially high set up costs ( $\gamma K(p)$ ) will foster a reduction of the ability level required in complex job ( $\delta_M < [a(\tilde{i}) + K(p)\gamma\{(1 - \beta(1 - \lambda)) - \frac{\beta\lambda}{1-\beta(1-\lambda)}(1 - \Phi(\varepsilon_{\tilde{i}}))\}]$ ). In contrast, as novel technologies become increasingly diffused, the effective reduction of the set up cost is likely to fall ( $\delta_M > [a(\tilde{i}) + K(p)\gamma\{(1 - \beta(1 - \lambda)) - \frac{\beta\lambda}{1-\beta(1-\lambda)}(1 - \Phi(\varepsilon_{\tilde{i}}))\}]$ ), favoring an increase in the firm's ability requirements,  $a(\hat{i})$ . During the rising path of  $p$  we are then likely to find an U-shaped trend of the ability level required in cognitive vacancies (see figures 12 and 13 in appendix D).

### With workers mobility

When unemployment benefits are not sufficient to compensate the low probability to find a job ( $\theta^S + \frac{\beta(1-\eta)}{c\eta}(w_S^u - w_M^u) > 0$ ), workers with an ability level above  $a(\tilde{i})$  prefer to search for a simple position even if they are endowed with an ability level above the one required by firms to fill complex vacancies. In this context, the endogenous segmentation of the labor market is given by  $a(\hat{i}) > a(\tilde{i})$ . All workers within the interval  $[a(\tilde{i}), a(\hat{i})]$  prefer to search for a job in the simple segment. The evolution of  $a(\hat{i})$  during the IT revolution is determined by the modification of the labor market tension in the simple segment as well as by the changes in the  $w_S^u - w_M^u$  relationship.

The rise in  $p$  yields a reduction of the equilibrium labor market tension in the simple segment since simple wages increase whereas productivity remains constant. Regarding the relationship

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<sup>18</sup>The effective variation in the set up costs must take into account the fact that not all complex positions manage to survive after the shock. On the other hand, notice that  $K(p)$  is decreasing in  $p$  and  $\gamma$  represents the speed of adjustment, implying that  $\gamma K(p)$  stands for the reduction in the costs derived from an increased diffusion of ICT. This reduction must then be corrected by the fraction,  $(1 - \Phi(\varepsilon_{\tilde{i}}))$ , of complex positions that does not manage to survive.

between the unemployment benefits, we find:

$$\frac{d}{dp} \frac{\beta(1-\eta)}{c\eta} (w_S^u - w_M^u) = \delta_S - \delta_M$$

As far as complex unemployment benefits are more indexed to  $p$  than simple unemployment benefits, which is likely to be the case, the divergence between the unemployment benefits paid in both labor market segments decreases along the ICT revolution.

Because the labor market tension in the simple segment and the divergence in the unemployment benefits decrease along the rising path of  $p$ ,  $\theta_i^M$  will tend progressively towards zero (it cannot become negative), implying that  $a(\hat{i})$  will converge towards  $a(\tilde{i})$ .

## 6 Numerical simulations

The quantitative implications of the model concerning the effects of a biased technological progress on the ability requirements to occupy complex jobs, on labor flows and on unemployment are clearly presented as results of computational exercises. The results reported in this section are based on the following additional specification assumptions. A matching function of the Cobb Douglas form is assumed with elasticity with respect to vacancies equal to  $\psi$ . The distribution of idiosyncratic shocks is assumed to be uniform on the support  $[\underline{\varepsilon}, \bar{\varepsilon}]$ , *i.e.*  $F(x) = (x - \underline{\varepsilon})/(\bar{\varepsilon} - \underline{\varepsilon})$ . The base line parameters used in computations are reported in table 5. The elasticity with respect to vacancies ( $\psi$ ), the bargaining power of workers ( $\eta$ ), the arrival rate of a productivity shock ( $\lambda$ ), the discount factor ( $\beta$ ), the recruiting cost ( $c$ ) are calibrated with the same values adopted by Mortensen and Pissarides (1994). All other structural parameters are chosen so that at the various steady states computed for different stages of technological diffusion, unemployment rates, job destruction rates and average duration of an unemployment spells match the average experience of France<sup>19</sup>. We compare this benchmark situation (French-type economy case) with a counterfactual one that would have arisen if the degree of indexation of the unemployment benefit had been lower. As in Mortensen and Pissarides (1994), the severance tax is assumed to be equal to 20% of the best productivity level it can be attained in a position (in appendix E we rewrite the equilibrium equations in the presence of a severance

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<sup>19</sup>At the final stage of the technological revolution, high-skilled workers support an unemployment rate at around 6% whereas the one of low-skilled workers reaches 20%. Yearly average complex job destruction rates equal 14% and those of simple jobs 27%. Finally, unemployment duration of high-skilled workers is less than six months whereas that of low qualified workers it is around a year and a half.

tax). We introduce this employment protection simply to keep as close as possible to the French case. When we eliminate it, our conclusions hold and there is only a scale effect.

	French-type High UB-EP	Low UB-EP
Unemployment benefit indexation: complex segment	$\delta_M = 0.65$	$\delta_M = 0.35$
Unemployment benefit indexation: simple segment	$\delta_S = 0.1$	$\delta_S = 0.05$
Severance tax	$T = 0.2$	$T = 0.2$
Discount factor	$r = 0.02$	
Matching elasticity	$\psi = 0.5$	
Bargaining power	$\eta = 0.5$	
Matching efficiency	$m_0 = 0.3$	
Recruiting cost	$c = 0.3$	
Productivity shock frequency	$\lambda = 0.1$	
Speed of the catch up process	$\gamma = 0.4$	
Deterministic productivity at simple jobs	$h = 1$	
Deterministic productivity at complex jobs	$p = 1$	

Table 5: Baseline parameter values.

We consider an initial situation where ICT are poorly present and all jobs are simple, so that workers of different abilities compete for the same positions. We then simulate the effects of a progressive diffusion of technologies (increase in  $p$  to attain  $p_0$ ) and analyze the evolution of the minimum skill level found in complex positions ( $a(\hat{i})$ ), the size of each labor market segment ( $\theta_i^M$  and  $\theta_i^S$ ), job stability ( $\varepsilon_i^M$  and  $\varepsilon_i^S$ ) and unemployment ( $u^M$  and  $u^S$ ).

Figure 5 summarizes the evolution of the minimum ability levels found in complex positions along the rising path of  $p$ . While during the first half of the IT revolution both economies display a similar decreasing path concerning the minimum ability level occupying complex positions (along this downward trend  $a(\hat{i}) > a(\tilde{i})$ ), from the second half of the IT revolution, the economy with high unemployment benefits sharply increases the skill requirements in cognitive positions. Furthermore, along this upward trajectory the firms skill requirements are binding, that is  $a(\hat{i}) = a(\tilde{i})$ . In spite of having a very low probability to find a job, medium-skilled workers in the neighborhood of  $\tilde{i}$  prefer to remain searching in the complex segment because the large unemployment benefits more than compensate their low probability to find a job. However, in the following stage of  $p$  these lowest ability slots are excluded from cognitive positions, since the upward trajectory of  $a(\hat{i}) = a(\tilde{i})$  implies that skill requirements increase.

The U-shaped path followed by skill requirements in cognitive positions, implies that, workers that previously qualified to these jobs do not longer have access to them and are then forced to

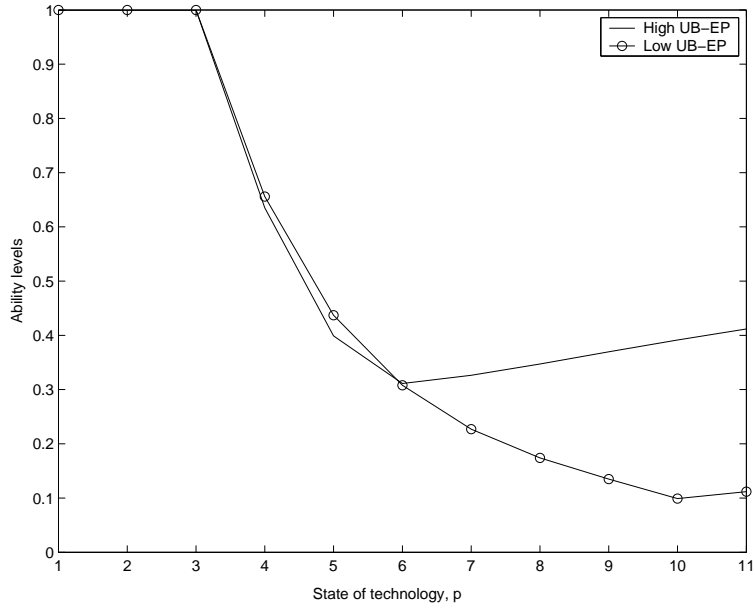


Figure 5: Evolution of the minimum skill level found in complex positions during the IT revolution.

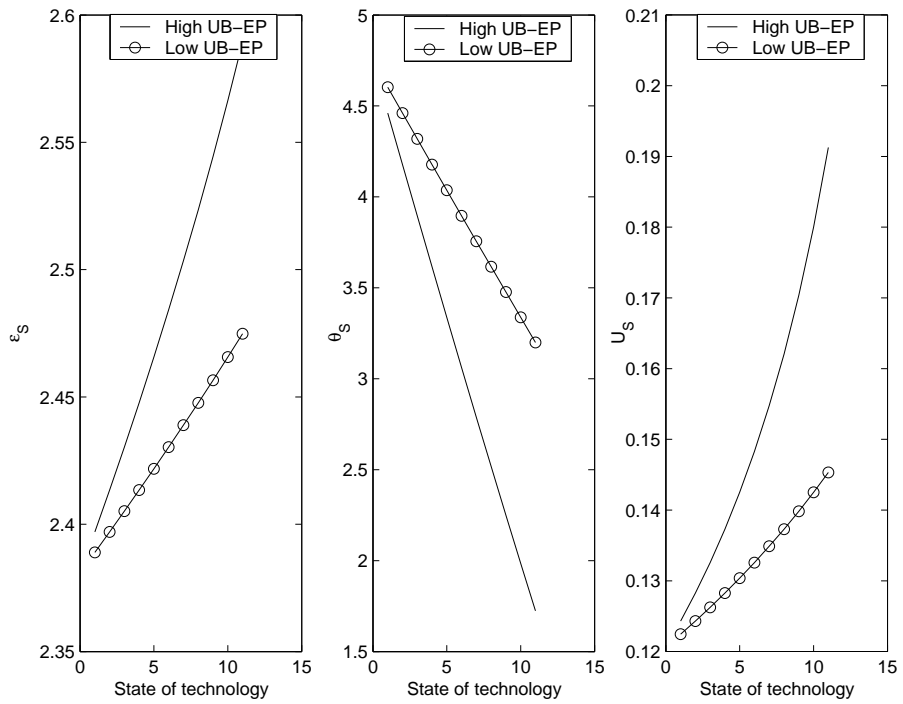


Figure 6: Evolution of job stability, labor market tension and unemployment rate in the simple segment during the IT revolution.



search in the simple segment where they enter in job competition with lower qualified workers. This U-shaped evolution is more pronounced in the French-type economy than in the economy where unemployment benefits are lower, where there is only a slight increase at the end of the rising path of  $p$ . The presence of high UB excludes therefore a larger fraction of workers from the complex segment and exacerbates job competition in the simple segment. Low UB allows a larger proportion of workers with heterogeneous abilities to have access to cognitive positions.

The evolution of job stability, labor market tensions and unemployment, is strongly differentiated depending on the considered labor market segment. In the simple segment (figure 6) job instability continuously increases whatever the type of economy considered. The labor market tightness of this segment is also progressively reduced, particularly rapidly when unemployment benefits are high. This sharp downturn in the labor market tension is reflected in unemployment rates. The diffusion of ICT does not simply contract the simple segment but it also deteriorates the situation of workers employed on it. This degradation is more important in the presence of high UB. Moreover, as displayed by figure 5, the proportion of workers concerned by these worse labor market conditions is more important in the French-type economy, where a larger fraction of workers is excluded from cognitive positions and must then occupy simple ones.

In the complex segment, the analysis must be done distinguishing between the highest ( $\bar{a}_i = 1$ ) ability level present in the segment and the lowest ability workers ( $a(\hat{i})$ ) employed in these jobs, which essentially corresponds to medium-skilled workers of the economy. Job stability and labor market tensions evolve very differently for both types of workers even if they are occupied in a same type of job. On the other hand, when comparing the complex segment of an economy characterized by high UB with the complex segment of an economy with low UB, we must consider that the proportion of workers employed in this segment is much smaller in the French-type economy.

Let's start with the evolution of job stability. Figure 7 displays in the x-axis the various states of technology and in the y-axis the reservation productivity level,  $\varepsilon_i^M$ , required to pursue a match. The line with circles displays the evolution of  $\varepsilon_i^M$  for  $i = 1$ , that is, for the highest ability slot present in the complex segment. The line with "+" envelops the critical productivity levels associated to the lowest ability level present in the complex segment at each stage of technology ( $a(\hat{i})$  or  $a(\tilde{i})$ ). Finally, the intermediate lines between the two previous ones, represent the evolution of the  $\varepsilon_i^M$  associated the minimum ability levels ( $a(\hat{i})$  or  $a(\tilde{i})$ ) that entered the complex segment at a given  $p$  and that remain for a while in it (they are not longer the lowest abilities

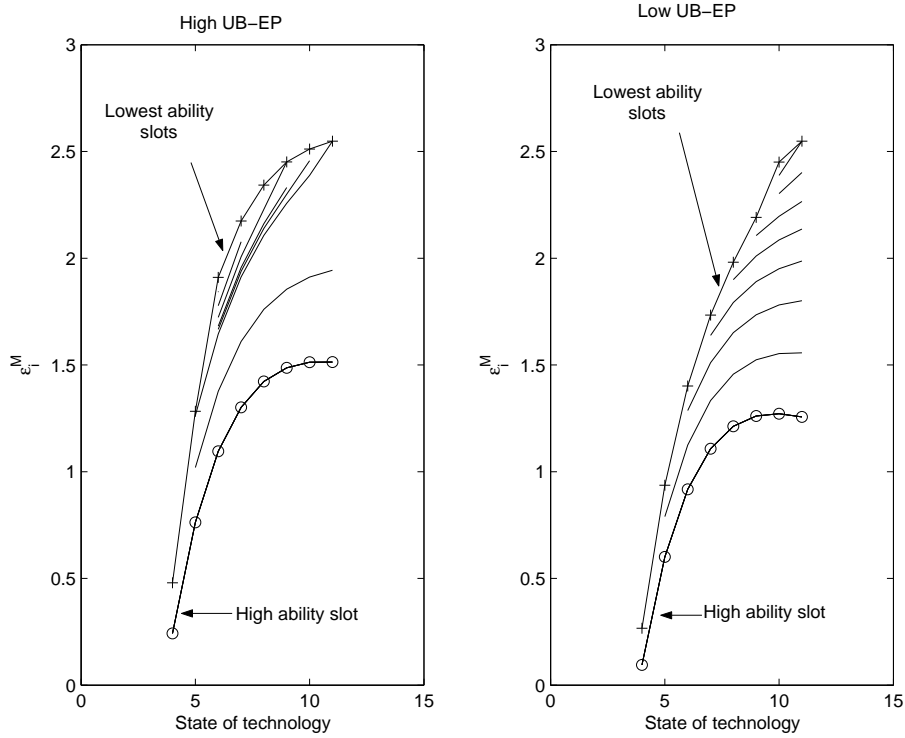


Figure 7: Evolution of job instability in the highest and the lowest ability slots of the complex segment during the IT revolution.

of the segment).

Comparing both economies (high UB vs. low UB) in figure 7, allows us to draw three conclusions. Firstly, for all  $p$  job instability is larger in an economy characterized by the generosity of unemployment benefits. Secondly, as novel technologies are diffused (increase in  $p$ ), all ability slots support a more important reservation productivity. However, the largest instability is supported by new entrants in the complex segment (medium-skilled workers). Finally, in the French-type economy, the reservation productivity levels associated to each of the ability slots are less dispersed than in the presence of low UB. Actually, we realize that in an economy characterized by low UB, there is a more important heterogeneity of ability levels occupying cognitive positions (see figure 5) but there is also a more important dispersion in the job stability supported by each these abilities.

Figure 8 presents the evolution of the labor market tension ( $\theta_i^M$ ) in various ability slots as  $p$  (state of technology) increases. More precisely, the line with circles stands for the evolution of  $\theta_1^M$ , that is, the labor market tension of the highest ability slot present in the complex segment. The rest of the lines correspond to the evolution of the labor market tension associated to those

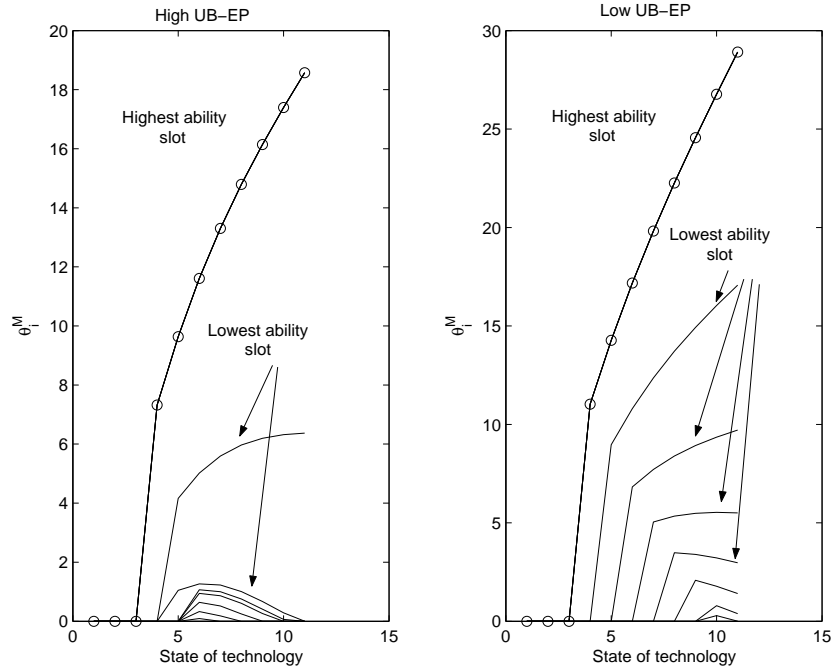


Figure 8: Evolution of the labor market tension of the highest and the lowest ability slots of the complex segment during the IT revolution.

ability levels ( $a(\hat{i})$  or  $a(\tilde{i})$ ) that entered the complex segment at a given state of technology and that remain then in this segment (they are not longer the lowest abilities of the segment). Because of the U-shaped evolution of the ability level present in complex positions, some slots appear and disappear during the ICT revolution. This yields an inverted U-shaped path for the labor market tension associated to some of the slots.

While  $\theta_i^M$  increases sharply and continuously for the highest ability level in both economies, the attained labor market tensions are more important in the presence of low UB. Concerning the rest of the ability levels, the more pronounced U-shaped path followed by the minimum ability level in the presence of high UB, is reflected on the inverted U-shape observed for the labor market tensions. In contrast, in the economy characterized by low UB, less workers are excluded from the complex segment (see figure 5), implying a more smoothed evolution of the labor market tensions associated to the lowest ability slots (the inverted U-shape is only observed at the end of the rising path of  $p$ ).

Figure 9 represents, by means of an histogram, the unemployment rates associated to all the ability slots present in the complex segment at each state of technology. The bars at the left of each histogram (associated to every stage  $p$ ) correspond to the unemployment rates of the

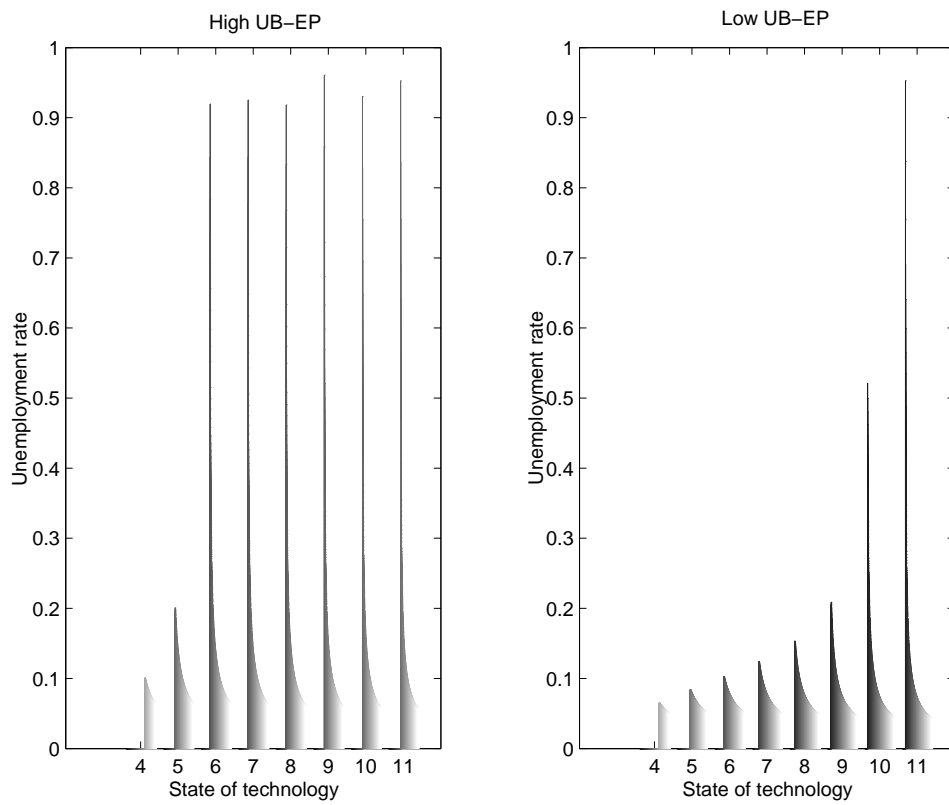


Figure 9: Evolution of unemployment in the highest and the lowest ability slots of the complex segment during the IT revolution.

lowest ability slots. These slots stand for much lower skill levels in the presence of low UB than in the presence of high UB (see figure 5). As a result, when comparing the histograms of both economies, we observe that those associated to the situation where UB are low are darker on their left hand side (they represent much more ability levels).

The most striking result when comparing both economies is that the unemployment rates supported by the lowest ability slots (of the complex segment) in the French-type economy become extremely high from the early stages of the technological revolution. In these economies, workers prefer to remain searching in the complex segment even if their probability to find a job converges to zero because unemployment benefits are very high. Actually, they remain in the complex segment until they are excluded from it by firms (when firms increase the skill requirement ( $a(\tilde{i})$ ) to fill a cognitive position). In contrast, in an economy characterized by low UB, the lowest ability workers prefer to search in the simple segment rather than supporting huge unemployment rates in the complex segment (the segmentation of this labor market is given by  $a(\hat{i})$ ). Unemployment rates in cognitive positions remain thus fairly moderate until the end of the rising path of  $p$ , when unemployment benefits become sufficiently large to compensate the low probability to find a job and workers decide thus to remain in the complex segment.

High unemployment benefits arise therefore as the main factor responsible for the large unemployment rates supported by medium qualified workers in complex positions. High UB reduce the incentive of these workers to search in the simple segment since it becomes more interesting for them to remain unemployed in the complex segment. Moreover, as previously underlined, in a French-type economy, these lowest ability slots correspond to medium qualified workers, whereas in an economy characterized by low unemployment benefits they stand for lower qualified workers.

Finally, concerning the situation of the highest ability slots in cognitive positions, the situation is fairly similar in both economies. Their associated unemployment rates remain moderate and stable along the rising path of  $p$ .

## 7 Conclusion

Information and communication technologies (ICT) have fostered a progressive job polarization in occidental labor markets between “lousy jobs”, traditionally occupied by low-skilled labor, and “lovely jobs”, generally filled by high-skilled workers. An empirical literature on the subject

starts to emerge, with authors like Autor et al. (2003), Goos and Manning (2003) or Spitz-Oener (2006), claiming that novel technologies are substitutes of cognitive routine tasks and complements of non routine cognitive tasks. However, to our knowledge, no theoretical framework analyzing the evolution of overeducation, job stability, number of vacancies and unemployment rates during this polarization process (fostered by ICT) has been developed. The present paper deals with this issue. More precisely, we consider the impact of labor market institutions in the evolution of the previous variables during the IT revolution.

We show that an endogenous job destruction framework where novel technologies asymmetrically affect productivity in simple and complex jobs, where unemployment benefits are indexed to aggregate productivity and where there are positive spillovers linked to the expansion of complex positions (reduction in the set up costs), is able to reproduce the U-shaped evolution followed by the minimum ability level occupied in complex vacancies. This trend forces workers that used to occupy complex positions to look for simpler jobs, stimulating job competition in this labor market segment. Furthermore, we show that the larger the redistributive component of the unemployment benefits, the larger the fraction of skills excluded from complex jobs.

The model also manages to capture the rapid appearance of non routine cognitive positions (the labor market tension in the complex segment increases much more at the highest ability slots) and disappearance of specialized jobs during the IT revolution. Concerning labor flows, simple positions suffer from a larger job instability, whereas people occupied in cognitive jobs may see their job stability increase or decrease depending on their ability level. Again, low ability workers employed in cognitive positions support a more important job instability during the diffusion process of novel technologies.

Finally, we find that the presence of high unemployment benefits leads workers in the neighborhood of the critical ability requirement to remain searching in the complex segment even if their probability to find a job is small. It is in their interest to remain unemployed in the complex segment rather than working in the simple one. As a result, medium qualified workers support high unemployment rates in economies characterized by high unemployment benefits. In contrast, in the presence of low unemployment benefits this phenomenon only arises at the very end of the technological revolution and it affects lower qualified workers than in the economy with high unemployment benefits.

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## 8 Appendix A

The French Labor Force Survey does not contain information on the skill requirements needed to perform a particular job. Nevertheless, each individual must specify the type of task implemented at her job. The survey distinguishes between 10 types of tasks:

- Task 1: Teaching, health services, information, others
- Task 2: Production, manufacture, roadwork, site work
- Task 3: Installing, repairing or renovating machines
- Task 4: Cleaning, garden work, housework
- Task 5: Handling, transport
- Task 6: Counter clerk, keyboarding, secretarial work
- Task 7: Management, accounts, administration functions
- Task 8: Trade, sales, clerk
- Task 9: Research, studies, informatics



- Task 10: Direction positions

The following table summarizes how the various positions we consider are composed:

Types of positions			
Cognitive/Complex positions		Manual/Simple positions	
Routine	Non Routine	Routine	Non Routine
People implementing task 7 and not having anyone under her orders	Task 1, 8, 9, 10. Task 7 if the worker has someone under her orders	Task 3, 4, 6.	Task 2, 5.

Table 6: Composition of the various types of positions.

## 9 Appendix B

We distinguish between the surplus associated to a first period job and the surplus associated to a continuing job:

$$S^M(a(i), \bar{\varepsilon}) = J^M(a(i), \bar{\varepsilon}) - V^M(a(i)) - K(p) + W^M(a(i), \bar{\varepsilon}) - U^M(a(i)) \quad \text{Joint surplus in the first period multitask job.}$$

$$S^M(a(i), \varepsilon) = J^M(a(i), \varepsilon) - V^M(a(i)) + W^M(a(i), \varepsilon) - U^M(a(i)) \quad \text{Joint surplus in a continuing multitask job.}$$

$$S^S(\bar{\varepsilon}) = J^S(\bar{\varepsilon}) - V^S + W^S(\bar{\varepsilon}) - U_i^S \quad \text{Joint surplus in a first period specialized job.}$$

$$S^S(\varepsilon) = J^S(\varepsilon) - V^S + W^S(\varepsilon) - U_i^S \quad \text{Joint surplus in a continuing specialized job.}$$

At the beginning of every period the firm and the employee renegotiate wages through a Nash bargaining process, that splits the joint surplus into fixed proportions at all times:

$$J^M(a(i), \bar{\varepsilon}) - V^M(a(i)) - K(p) = (1 - \eta) S^M(a(i), \bar{\varepsilon}) \quad \text{or} \quad W^M(a(i), \bar{\varepsilon}) - U^M(a(i)) = \eta S^M(a(i), \bar{\varepsilon}), \quad (28)$$

$$J^M(a(i), \varepsilon) - V^M(a(i)) = (1 - \eta) S^M(a(i), \varepsilon) \quad \text{or} \quad W^M(a(i), \varepsilon) - U^M(a(i)) = \eta S^M(a(i), \varepsilon), \quad (29)$$

$$J^S(\bar{\varepsilon}) - V^S = (1 - \eta) S^S(\bar{\varepsilon}) \quad \text{or} \quad W^S(\bar{\varepsilon}) - U_i^S = \eta S^S(\bar{\varepsilon}), \quad (30)$$

$$J^S(\varepsilon) - V^S = (1 - \eta) S^S(\varepsilon) \quad \text{or} \quad W^S(\varepsilon) - U_i^S = \eta S^S(\varepsilon). \quad (31)$$

### 9.0.3 The surplus

Using equations (4)-(11) and knowing that at the equilibrium the firm opens vacancies until no more profit can be obtained, *i.e.*  $V^M(a(i)) = 0$  and  $V^S = 0$ , we develop the following expressions for the surplus associated to a complex and to a simple job, respectively:

$$S^M(a(i), \bar{\varepsilon}) = p \cdot a(i) + \bar{\varepsilon} - w_M^u - K(p)(1 - \beta(1 - \lambda)) + \beta(1 - \lambda) \text{Max}[S^M(a(i), \bar{\varepsilon}), 0] + \beta\lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \text{Max}[S^M(a(i), \varepsilon), 0] d\Phi(x) - \frac{\eta}{1 - \eta} c \theta_i^M, \quad (32)$$

$$S^M(a(i), \varepsilon) = p \cdot a(i) + \varepsilon - w_M^u + \beta(1 - \lambda) \text{Max}[S^M(a(i), \varepsilon), 0] + \beta\lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \text{Max}[S^M(a(i), \varepsilon), 0] d\Phi(x) - \frac{\eta}{1 - \eta} c \theta_i^M, \quad (33)$$

$$S^S(\bar{\varepsilon}) = h + \bar{\varepsilon} - w_S^u + \beta(1 - \lambda) \text{Max}[S^S(\bar{\varepsilon}), 0] + \beta\lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \text{Max}[S^S(x), 0] d\Phi(x) - \frac{\eta}{1 - \eta} c \theta^S, \quad (34)$$

$$S^S(\varepsilon) = h + \varepsilon - w_S^u + \beta(1 - \lambda) \text{Max}[S^S(\varepsilon), 0] + \beta\lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} \text{Max}[S^S(x), 0] d\Phi(x) - \frac{\eta}{1 - \eta} c \theta^S, \quad (35)$$

where  $\frac{\partial S^M(a(i), \varepsilon)}{\partial \varepsilon} = \frac{1}{1 - \beta(1 - \lambda)} > 0$  for  $\varepsilon \geq \varepsilon_i^M$ , and  $\frac{\partial S^S(\varepsilon)}{\partial \varepsilon} = \frac{1}{1 - \beta(1 - \lambda)} > 0$  for  $\varepsilon \geq \varepsilon^S$ .

### 9.0.4 The wages

At the beginning of every period wages are negotiated between the worker and the firm according to the Nash sharing rules:

$$J^M(a(i), \bar{\varepsilon}) - V^M(a(i)) - K(p) = \frac{(1 - \eta)}{\eta} [W^M(a(i), \bar{\varepsilon}) - U^M(a(i))], \quad (36)$$

$$J^M(a(i), \varepsilon) - V^M(a(i)) = \frac{(1 - \eta)}{\eta} [W^M(a(i), \varepsilon) - U^M(a(i))], \quad (37)$$

$$J^S(\bar{\varepsilon}) - V^S = \frac{(1 - \eta)}{\eta} [W^S(\bar{\varepsilon}) - U_i^S]. \quad (38)$$

$$J^S(\varepsilon) - V^S = \frac{(1 - \eta)}{\eta} [W^S(\varepsilon) - U_i^S]. \quad (39)$$

Lindquist (2002) demonstrates that, except from the wage profile, this bitemporal specification of wage negotiation in the complex segment is equivalent to just assuming (37) for all periods. He shows that the present value of a worker's total compensation for any completed job is the

same which, in turn, implies the same present value of a firm's pay off. In both specifications the equilibrium allocation of labor is the same in spite of the different bargaining formulations. Substituting the value functions into the previous equations yields the following wage expression (see Pissarides (2000) chapter 2):

$$w^M(a(i), \bar{\varepsilon}) = (1 - \eta) w_M^u + \eta(p \cdot a(i) + \bar{\varepsilon} + c\theta_i^M - K(p)(1 - \beta(1 - \lambda))), \quad (40)$$

$$w^M(a(i), \varepsilon) = (1 - \eta) w_M^u + \eta(p \cdot a(i) + \varepsilon + c\theta_i^M), \quad (41)$$

$$w^S(\bar{\varepsilon}) = (1 - \eta) w_M^u + \eta(h + \bar{\varepsilon} + c\theta^S), \quad (42)$$

$$w^S(\varepsilon) = (1 - \eta) w_M^u + \eta(h + \varepsilon + c\theta^S). \quad (43)$$

Following Lindquist (2002), in the complex segment of the labor market we keep (41) as wage equation.

Workers within the interval  $[a(\tilde{i}), a(\hat{i})]$  have the required ability to occupy a cognitive position. However, given the labor market tensions in each segment and the unemployment benefits, it is in their interest to search rather for a simple position. During their first period of search, their outside option equals though  $w_M^u$ , implying that their bargained wages with the simple firm must differ from those obtained by workers with an ability level  $a(i) < a(\tilde{i})$ . Let's denote by the subindex  $H$  the asset values associated to the situation where the simple job is filled by someone with an ability level inside  $[a(\tilde{i}), a(\hat{i})]$  :

$$U_H^S = w_M^u + \beta(1 - \theta^S q(\theta^S))U_H^S + \beta\theta^S q(\theta^S)W_H^S(\bar{\varepsilon}) \quad (44)$$

$$W_H^S(\bar{\varepsilon}) = w_H^S(\bar{\varepsilon}) + \beta(1 - \lambda)Max[W_H^S(\bar{\varepsilon}), U^S] + \beta\lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} Max[W_H^S(x), U^S]d\Phi(x) \quad (45)$$

$$J_H^S(\bar{\varepsilon}) = h + \bar{\varepsilon} - w_H^S(\bar{\varepsilon}) + \beta(1 - \lambda)Max[J_H^S(\bar{\varepsilon}), V^S] + \beta\lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} Max[J_H^S(x), V^S]d\Phi(x) \quad (46)$$

$$V^S = -c + \beta(1 - q(\theta^S))V^S + \beta q(\theta^S)J_H^S(\bar{\varepsilon}) \quad (47)$$

$$(48)$$

We assume that firms cannot discriminate among workers so that as far as the surplus is positive a match is formed. The surplus associated to this type of matches is thus given by  $S_H^S(\bar{\varepsilon}) = J_H^S(\bar{\varepsilon}) - V^S + W_H^S(\bar{\varepsilon}) - U_H^S$ . Because  $U^S \leq U_H^S$ , at the equilibrium the surplus is given by:

$$S_H^S(\varepsilon) = h + \varepsilon - w_M^u + \beta(1 - \lambda)S_H^S(\varepsilon) + \beta\lambda \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} (1 - \Phi(x))dx \quad (49)$$

Applying the Nash sharing rule, we obtain the following expression for the first period wage :

$$w_H^S(\bar{\varepsilon}) = (1 - \eta)w_M^u + \eta(h + \varepsilon + c\theta^S) \quad (50)$$

As previously, we can ignore this first period wage, since the firm knows that after one period, the high skilled worker's outside option becomes  $w_S^u$ , therefore she will directly offer a wage taking as reference this threat point.

### 9.0.5 The labor market flows and the equilibrium rate of unemployment

We normalize the total labor force to one and assume an ability distribution function  $G'(a(i)) = g(a(i))$ . Total unemployment is then given by:

$$U = \int_{\underline{a}}^{\bar{a}} u_i g(a(i)) di \quad (51)$$

We first focus our attention on the labor flows affecting people having an ability level above the threshold value  $a(\hat{i})$  and effectively searching a complex job, that is, we focus on people with an ability level  $a(i) > a(\hat{i})$ . The number of people of this ability slot employed in period  $t$  equals  $g(a(i)) - u_i$ . We know that every period there is a probability  $\lambda$  that a shock arrives so that a new value of  $\varepsilon$  is drawn from the probability distribution  $\Phi$ . If the novel value is below the reservation productivity level  $\varepsilon_i^M$  the job is destroyed. The inflows to unemployment in period  $t$  are hence equal to  $[g(a(i)) - u_i] \lambda \Phi(\varepsilon_i^M)$ . On the other hand, the number of people with ability  $a(i) > a(\hat{i})$  quitting unemployment equals  $u_i p(\theta_i^M)$ .

In the steady state outflows from unemployment are identical to inflows, implying the following equilibrium equation:

$$[g(a(i)) - u_i] \lambda \Phi(\varepsilon_i^M) = u_i p(\theta_i^M) \quad \forall i \geq \hat{i} . \quad (52)$$

The number of unemployed workers with a particular skill level  $a(i)$  above  $a(\hat{i})$  is then given by:

$$u_i = \frac{\lambda \Phi(\varepsilon_i^M) g(a(i))}{\lambda \Phi(\varepsilon_i^M) + p(\theta_i^M)} \quad \forall i \geq \hat{i} \quad (53)$$

The situation on the segment of workers with ability level below  $a(\hat{i})$  is somewhat different. In this segment we assume undirected search (the open vacancy does not seek a particular ability level). The number of employed workers with a skill level smaller than  $a(\hat{i})$  is given by  $G(a(\hat{i})) - U_s$ , where  $G(a(\hat{i}))$  stands for all workers having an ability level below  $a(\hat{i})$  and  $U_s$  represents the number of these workers being unemployed. Every period a proportion  $\lambda \Phi(\varepsilon^S)$  of simple jobs is destroyed, implying an inflow into unemployment equal to:  $(G(a(\hat{i})) - U_s) \lambda \Phi(\varepsilon^S)$ . At the same time, every period, a proportion  $p(\theta^S)$  of unemployed with an ability level below  $a(\hat{i})$  finds a specialized job, implying an outflow from unemployment equal to  $U_s p(\theta^S)$ .

At the steady state the inflows and outflows from unemployment must be identical:

$$(G(a(\hat{i})) - U_s)\lambda\Phi(\varepsilon^S) = U_s p(\theta^S) \quad \forall i \leq \hat{i}. \quad (54)$$

leading to the following equilibrium unemployment  $\forall i \leq \hat{i}$ :

$$\frac{U_s}{G(a(\hat{i}))} = \frac{\lambda\Phi(\varepsilon^S)}{p(\theta^S) + \lambda\Phi(\varepsilon^S)} \quad (55)$$

Aggregate unemployment can be obtained through the addition of low-skill and high-skill unemployment (equations (53) and (55)).

$$\begin{aligned} U &= U^s + \int_{a(\hat{i})}^{\bar{a}} u(a(i))g(a(i))da(i) \\ &\equiv u^s \int_{\underline{a}}^{a(\hat{i})} g(a(i))da(i) + \int_{a(\hat{i})}^{\bar{a}} u(a(i))g(a(i))da(i) \\ &= \int_{\underline{a}}^{\bar{a}} u(a(i))g(a(i))da(i) \end{aligned} \quad (56)$$

where  $u(a(i)) = u^s \forall i \leq \hat{i}$ . Because  $a(\hat{i})$ , the labor market tightness and the critical productivity levels are known, we can directly determine the equilibrium unemployment levels.

## 10 Appendix C

**Proof: The positive slope of the specialized job destruction curve.**

We analyze the slope of the job destruction curve by differentiating equation (15) with respect to  $\varepsilon^S$ :

$$\begin{aligned} \frac{\eta c}{1-\eta} \frac{\partial \theta^S}{\partial \varepsilon^S} &= 1 + \frac{\beta \lambda}{1-\beta(1-\lambda)} \frac{\partial}{\partial \varepsilon^S} \int_{\varepsilon^S}^{\bar{\varepsilon}} (1-\Phi(x))dx, \\ &= 1 + \frac{\beta \lambda}{1-\beta(1-\lambda)} \left( -\frac{\partial}{\partial \varepsilon^S} \int_{\bar{\varepsilon}}^{\varepsilon^S} (1-\Phi(x))dx \right), \\ &= 1 - \frac{\beta \lambda}{1-\beta(1-\lambda)} (1-\Phi(\varepsilon^S)). \end{aligned} \quad (57)$$

From the previous expression we realize that:

$$\text{sign} \frac{\partial \theta^S}{\partial \varepsilon^S} = \text{sign} \left( 1 - \frac{\beta \lambda}{1-\beta(1-\lambda)} (1-\Phi(\varepsilon^S)) \right) \quad (58)$$

We proceed then to determine the sign of the right hand side of equation (58). Because  $0 < \beta < 1$  we know that  $1 - \beta + \beta \lambda > \beta \lambda$ . Therefore:

$$0 < \frac{\beta \lambda}{1 - \beta(1 - \lambda)} < 1 .$$

At the same time, since  $\Phi(x)$  is a probability distribution function we have that  $0 \leq 1 - \Phi(\varepsilon^S) \leq 1$ . Multiplying two positive numbers smaller than one leads to a positive number smaller than one, so that:

$$1 - \frac{\beta \lambda}{1 - \beta(1 - \lambda)}(1 - \Phi(\varepsilon^S)) > 0 \quad \text{which implies} \quad \frac{\partial \theta^S}{\partial \varepsilon^S} > 0 . \quad (59)$$

The job destruction curve is thus positive sloped. ■

**Proof: The negative slope of the specialized job creation curve.**

To determine the sign of the slope of the job creation curve we differentiate equation (17) with respect to  $\varepsilon^S$ :

$$\begin{aligned} -\frac{c(1 - \beta(1 - \lambda))}{\beta(1 - \eta)} \frac{q'(\theta^S)}{q^2(\theta^S)} \frac{\partial \theta^S}{\partial \varepsilon^S} &= -\frac{\partial \varepsilon^S}{\partial \varepsilon^S} , \\ -\frac{c(1 - \beta(1 - \lambda))}{\beta(1 - \eta)} \frac{q'(\theta^S)}{q^2(\theta^S)} \frac{\partial \theta^S}{\partial \varepsilon^S} &= -1 , \\ \frac{c(1 - \beta(1 - \lambda))}{\beta(1 - \eta)} \frac{q'(\theta^S)}{q^2(\theta^S)} \frac{\partial \theta^S}{\partial \varepsilon^S} &= 1 , \end{aligned}$$

Because  $0 < \beta < 1$ ,  $0 < \eta < 1$  and  $c > 0$  the first term on the left hand side,  $\frac{c(1 - \beta(1 - \lambda))}{\beta(1 - \eta)}$ , is positive. Therefore:

$$\text{sign} \frac{\partial \theta^S}{\partial \varepsilon^S} = \text{sign} \frac{q^2(\theta^S)}{q'(\theta^S)} \quad (60)$$

As  $q^2(\theta^S)$  is always positive and the probability of filling a vacancy is a decreasing function on the labor market tightness ( $q'(\theta^S) < 0$ ), we find that  $\frac{q^2(\theta^S)}{q'(\theta^S)} < 0$ . The specialized job creation curve is negatively sloped. ■

## 11 Appendix D: A skill-biased technological shock

### 11.1 Simple jobs

The equilibrium in the simple segment is characterized by two equations, the job destruction and job creation curves, respectively given by (15) and (17). A variation in  $p$  shifts up the job destruction curve (see figure 10), determining a new equilibrium where the reservation productivity is higher and the labor market tightness lower.

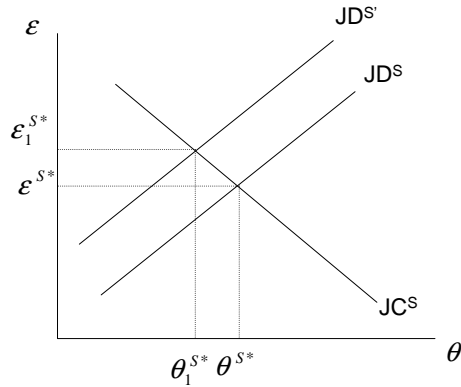


Figure 10: Effects of a biased technological in the specialized segment.

### 11.2 Complex jobs

Combining the movement of the complex job creation curve and the one of the complex job destruction curve, we can distinguish between three possible situations. If  $a(i)$  equals  $\delta_M$  or is nearby, the new equilibrium will be characterized by a higher reservation productivity and labor market tension (see case A figure 11). For high ability levels, productivity gains ( $pa(i)$ ) in case of technological shock largely compensate the rise in wages ( $p\delta_M$ ), leading to a new equilibrium where the number of vacancies increases (higher labor market tension) and the reservation productivity falls (case B figure 11). Finally, for a “sufficiently small” ability level, the job destruction curve moves upward fostering a fall in the labor market tension and a rise in the critical productivity level required to pursue the match (case C figure 11). However, this shift is downward bounded by  $\theta_i^M = \theta^S + \frac{\beta(1-\eta)}{c\eta}(w_S^u - w_M^u)$  (vertical line  $B$  in figure 11), since all individuals in an ability slot having a labor market tension below this bound will prefer to search in the simple segment. The complex segment disappears thus from this threshold ability level  $a(\hat{i})$ .

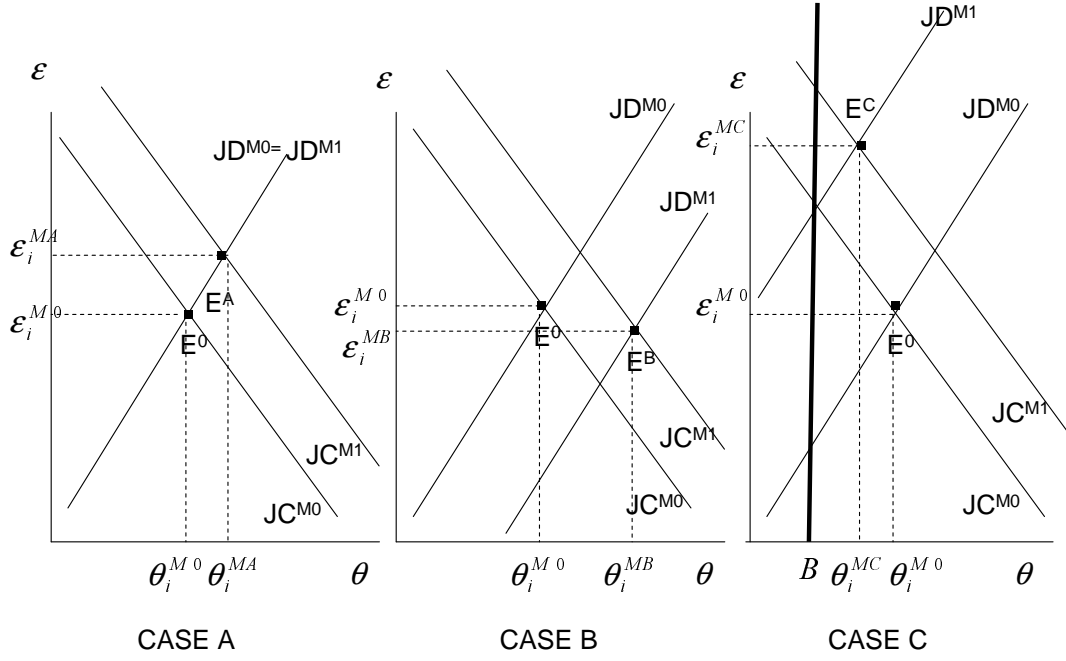


Figure 11: Effects of a biased technological on the job creation and job destruction curves for  $a(i) > a(\tilde{i})$ .

For  $\theta_i^M = 0$ , a progressive rise in  $p$  promotes the upward shift of the job creation curve and the rightward rotation of the job destruction. As remarked in the text, for reasonable parameter values, we expect that the initial increases in  $p$  yield a reduction in the critical ability level required for cognitive jobs (figure 12), whereas for already high values of  $p$  we expect that additional increases favor an upturn in this critical ability level (figure 13).

## 12 Appendix E

Let's denote as TC and TS the severance tax (employment protection) paid by the firm for a complex and simple position, respectively. When introducing them in the model, the equilibrium equations become:



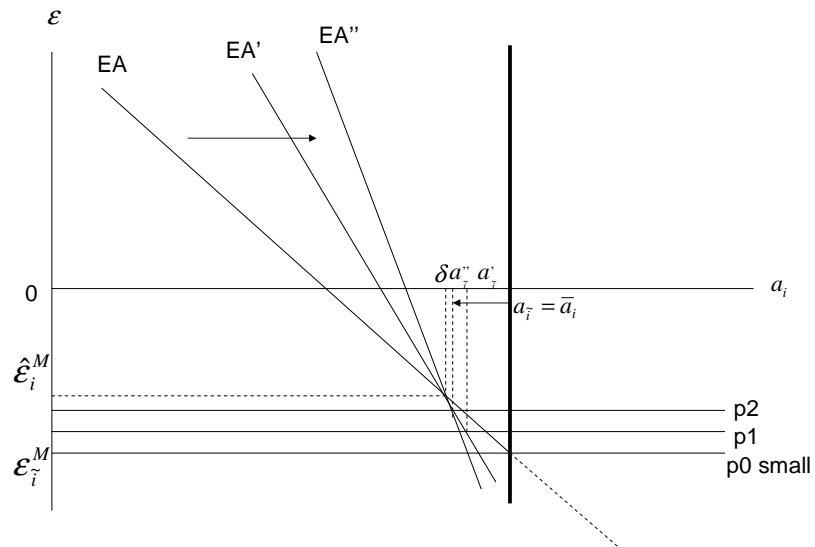


Figure 12: Effects of a biased technological in the multitask segment : Low  $p$ .

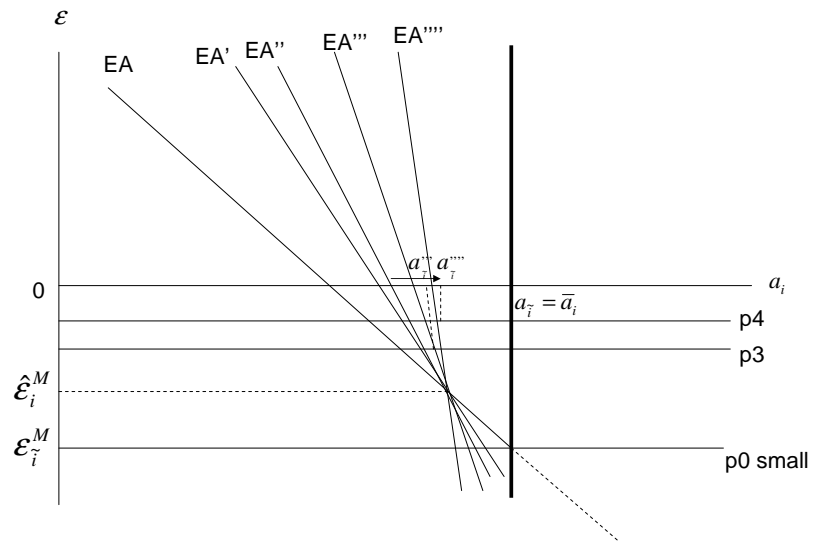


Figure 13: Effects of a biased technological in the complex segment : High  $p$ .

$$\frac{\eta}{1-\eta}c\theta_i^M = p \cdot (a(i) - \delta) + \varepsilon_i^M + TC(1 - \beta) + \frac{\beta \lambda}{1 - \beta(1 - \lambda)} \int_{\varepsilon_i^M}^{\bar{\varepsilon}} (1 - \Phi(x))dx, \quad (61)$$

$$\frac{\eta}{1-\eta}c\theta^S = h - w_S^u + \varepsilon^S + TS(1 - \beta) + \frac{\beta \lambda}{1 - \beta(1 - \lambda)} \int_{\varepsilon^S}^{\bar{\varepsilon}} (1 - \Phi(x))dx, \quad (62)$$

$$\frac{c}{\beta q(\theta_i^M)} = (1 - \eta) \left[ \frac{(\bar{\varepsilon} - \varepsilon_i^M)}{1 - \beta(1 - \lambda)} - K(p) - TC \right], \quad (63)$$

$$\frac{c}{\beta q(\theta^S)} = (1 - \eta) \left[ \frac{(\bar{\varepsilon} - \varepsilon^S)}{1 - \beta(1 - \lambda)} - TS \right]. \quad (64)$$

where  $K(p) = e^{-\gamma(p-p_0)}$ .