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Age Biased Technical and Organisational Change, Training and Employment Prospects of Older Workers*

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Résumé

Nous analysons dans quelle mesure la formation peut atténuer les effets défavorables pour l'emploi des seniors du changement technologique et organisationnel. A partir d'un panel d'entreprises françaises suivies sur seconde moitié des années 1990, nous confirmons le caractère biaisé des nouvelles technologies et de certaines pratiques de travail innovantes à l'encontre des salariés âgés. Internet et l'adoption d'ordinateurs connectés en réseau ainsi que l'élargissement des responsabilités confiées aux opérateurs tendent à accroître la part des trentenaires et à réduire celle des seniors dans la masse salariale. En revanche, le raccourcissement de la chaîne de commandement sous la forme d'une réduction du nombre de niveaux hiérarchiques est favorable aux seniors. La formation continue contribue à protéger les seniors en termes d'emploi et/ou de rémunérations.

Mots clés: Changement technologique ; changement organisationnel ; formation ; travailleurs seniors.

JEL codes: J14; J24; J26; O30.

Abstract

We analyze the role of training in mitigating the negative impact of technical and organizational changes on the employment of older workers. Using a panel of French firms in the late 1990s, our empirical analysis confirms that new technologies and some innovative workplace practices are biased against older workers. The use of the Internet and the adoption of computer networks tend to increase the wage share of middle-aged workers and to reduce the share of workers older than 50. By contrast, the reduction of the number of hierarchical layers is favourable to older workers. Training contributes to protect older workers in terms of employment and/or of wages.

Keywords: Technical change; organizational change; training; older workers.

JEL codes: J14; J24; J26; O30.

INTRODUCTION

In most European countries, population has been ageing quickly in recent years and this trend is not expected to revert in the near future. A direct consequence of this has been the increase in the ratio of retirees to working population, which has generated in turn growing budget unbalances in the pension systems. In order to reduce the resulting deficits, many governments have increased the legal age of retirement, hoping that this would decrease the retiree-to-working-population ratio. The success of such policy crucially depends of course on whether older workers are able to find a job or at least stay in employment (see Boldrin et al, 1999). So, it raises the issue of the demand for labour addressed by firms to older workers.

There is evidence in the literature that the demand for older workers has been negatively affected by the rapid development of information and communication technologies (ICT) and of innovative work practices in the past decades (see Aubert et al, 2006, Beckmann, 2007 and Ronningen, 2007). Underlying this process is the fact that ICT accelerate skill obsolescence. Given that older workers have completed their education less recently than younger ones, they are more affected by the loss of competence. In this context, continuous training becomes a key policy instrument to foster the employability of older workers. The question we tackle in this paper is: how efficient is continuous training in improving the employment prospects of older workers in an environment characterised by the development of new technologies and innovative work practices?

In order to answer this question, we first estimate wage bill share equations for different age groups. In order to control for unobserved heterogeneity and potential reverse causality we estimate long difference equations in which the change in the wage bill share of each age group is a function of the change in ICT and innovative work practices lagged one period and training lagged one period. Consistent with what is found in the literature, we find that adopting new technologies and innovative work practices negatively affects the wage bill share of older workers. In contrast, training older workers more than average increases their share in the wage bill in the next period. So, training contributes to offset the negative impact of ICT and innovative work practices. However, it does not reduce the age bias associated with these innovative devices: the interaction terms between training and ICT/innovative work practices are either insignificant or negative. As a second step, we estimate the impact of ICT, innovative work practices and training on employment flows by age group in the next period. We get similar results to those obtained with wage bill shares. Innovative devices negatively affect older workers with respect to other age groups either because they increase hirings in a smaller proportion or because they raise separations more than average. In contrast, training protects older workers by reducing inflows of competing age groups. Overall, training appears to have a positive impact on the employability of older workers, but it offers limited prospects to dampen the age bias associated with new technologies and innovative work practices.

Our paper contributes to the now vast literature on age biased technical change. The idea that technological and organisational changes negatively affect older workers has been tested in various ways in the literature. A first strand of papers investigates whether age has a negative impact on computer use. On UK data, Borghans and Ter Weel (2002) find no evidence of such phenomenon. In contrast, Friedberg (2003) finds partial evidence of skill obsolescence in the USA, with technological change in a worker's environment having a negative impact on computer use, but only for workers close to retirement. For Germany, Schleife (2006) finds a strong and negative correlation between workers' age and computer use. Similar results are found for the Netherlands by Koning and Gelderblom (2006). However, these studies are flawed by selection bias. If workers who are less able to adapt to new technologies and innovative work practices have already retired or been laid-off, the effect of age will be underestimated when looking at how it correlates with computer use. A second empirical strategy has therefore consisted in estimating the impact of computer use on retirement decisions. On U.S. data, Bartel and Sicherman (1993) show that workers in industries with a higher rate of technological change tend to retire later. However, unexpected changes in the rate of technological change induce workers to retire earlier. Similar results are obtained by Haegeland et al (2007) for Norway. A last strand of papers have taken a different view and investigated the impact of the introduction of ICT and innovative work practices on firm's labour demand for older workers (Aubert et al, 2006, Beckmann, 2007, Ronningen, 2007). They all find that the introduction of innovative devices negatively affects the wage bill share of older workers. Our paper uses the same methodology. We also find evidence of age biased technical and organisational change and extend the analysis to consider the potential role of training in this adjustment.

Our work also contributes to the literature on the impact of training on the employability of older workers. Not much has been done so far on this issue. Using subjective data on job security, Bassanini (2006) provides evidence that training taken with the previous employer has a positive impact on the perceived job security of older workers. Schleife (2008) uses a more objective measure of employability and shows that the proportion of older workers receiving IT training is positively correlated with their share in employment three years later. Similar results are found by Behaghel et al (2010). Similarly, Picchio and Van Ours (2011) find that older workers who receive training are more likely to remain employed. The question we ask in this paper is: is this effect of training strong enough to dampen the age bias associated with the introduction of ICT and innovative work practices? For Germany, Schleife (2008) finds that the positive correlation between IT training provided to older workers and their share in employment is strongest in IT-intensive industries whereas it is insignificant in less IT-intensive ones. Song (2009) suggests that training could actually harm older workers in a context of rapid development of ICT if it is firm specific. On CPS data, he finds that the probability of displacement by position abolition increases with age, ICT use within an occupation/industry and with the provision of specific training by the employer. Based on these results, he conjectures that firm specific training may undermine job security of older workers in a context of rapid technological changes. The reason for this would be that technological change depreciates the existing stock of firm-specific human capital thus leading firms to dismiss workers because they find it unprofitable to retrain them. We test whether the employment prospects of older workers are better or worse when the introduction of innovative devices is combined with training. We find that although training increases the share of older workers in employment and reduces their turnover it is not strong enough to dampen the age bias associated with ICT and innovative work practices.

The layout of the rest of the paper is as follows. Section I presents the econometric model. Section II describes the data. Section III reports the results and Section IV concludes.

I. THE ECONOMETRIC MODEL

In order to study the relationships between training and the wage bill shares of the various age groups in innovative firms, we use a classical labour demand framework. As is standard in the literature, we assume that the cost function is a restricted *translog* (see for example Caroli and Van Reenen, 2001).

Wage bill shares

Since we are interested in the joint effects of training and innovation on the age structure of the workforce, we assume that the only variable factors are the different types of labour as characterised by their age and indexed by *a*. Correspondingly, we assume that capital is a "quasi-fixed" factor which varies only in the long run and can therefore be considered as exogenous in the short run.

Under these assumptions, the wage bill shares of the various age groups are as follows – see Aubert et al (2006):

$$S_{a,i,t} = \alpha_a + \sum_{a' \in \{1...A\}} \gamma_{a,a'} \ln(W_{a'})_{it} + \gamma_{a,K} \ln(K)_{it} + \gamma_{a,TECH}.\ln(TECH)_{it} + \gamma_{a,HK}.\ln(HK)_{it} + \gamma_{a,VA} \ln(VA)_{it} + \gamma_{a,Z}.Z_{it} + \varepsilon_{a,i,t} \quad (1)$$

where $S_{a,i,t}$ denotes the wage bill share of age group *a* in firm *i* at date *t*, *K* the stock of physical capital, *VA* the value-added of the firm, $W_{a'}$ the hourly wage of age group *a'*, *Z* a vector of industry and size dummies, and $\varepsilon_{a,i}$ an error term. We assume that the stock of capital of the firm also encompasses technological capital (*TECH*) and human capital (*HK*). *TECH* captures the use of information and communication technologies and/or innovative work practices and *HK* captures the stock of human capital – potentially specific to each age group – used in the production process. The total number of age groups is *A*.

Since we consider the system of wage bill share equations for all age groups, we need to place additional restrictions on the parameters in order to make sure that all shares sum up to 1. Symmetry implies that:

$$\gamma_{a,a'} = \gamma_{a',a}$$

and homogeneity implies that:

$$\sum_{a=1}^{A} \alpha_a = 1 \text{ and } \sum_{a=1}^{A} \gamma_{a,u} = 0 \ \forall\ u \in U = \{u = 1,..., A; VA; K; TECH; HK; Z\}.$$

Given that the wage bill shares of the various age groups sum up to 1, one of the equations becomes redundant. So, we estimate the system for all age categories *a* but the first one. The model becomes:

$$S_{a,i,t} = \alpha_a + \sum_{a' \in \{2...A\}} \gamma_{a,a'} \ln(W_{a'}/W_1)_{it} + \gamma_{a,K} \ln(K)_{it} + \gamma_{a,TECH} \ln(TECH)_{it} + \gamma_{a,HK} .\ln(HK)_{it}$$
$$+ \gamma_{a,VA} \ln(VA)_{it} + \gamma_{a,Z} .Z_{it} + \varepsilon_{a,i,t} \quad \forall\, a \in \{2...A\} \tag{2}$$

The youngest age group (indexed by 1) is taken as the reference in order to compute relative wages $\ln(W_{a'}/W_1)_i$ and is therefore eliminated from the equation system. This age group corresponds to workers aged 20 to 29 years old (see Section II).

A first problem in estimating equations (2) has to do with unobserved heterogeneity: unobserved firm characteristics could affect both the age structure of the workforce and the innovation and training strategies of the firms. In order to deal with this problem, we estimate the model in long differences which allows us to difference out any time-invariant unobservable factor. Our specification is as follows:

$$\Delta S_{a,i,t+1} = \sum_{a' \in \{2...A\}} \gamma_{a,a'} \Delta \ln(W_{a'}/W_1)_{it} + \gamma_{a,K} \Delta \ln(K)_{it} + \gamma_{a,INNOV} INNOV_{it} + \gamma_{a,TRAIN} .TRAIN_{it}$$
$$+ \gamma_{a,VA} \Delta \ln(VA)_{it} + \sum_{a' \in \{1...A\}} \zeta_{a'} P_{a',i,t-1} + \gamma_{a,Z} .Z_{it} + \varepsilon_{a,i,t} \quad \forall\, a \in \{2...A\} \tag{3}$$

where $\Delta S_{a,i,t+1}$ is the change in the wage bill share of the various age groups, $\Delta \ln(K)_{it}$ the change in the log of the physical capital stock, $\Delta \ln(VA)_{it}$ the change in the log of value-added, $\Delta \ln(W_{a'}/W_1)_{it}$ the change in relative wages. Z_{it} is our vector of controls including size and industry dummies. $INNOV_{it}$ captures the introduction of information and communication technologies and/or innovative work practices and is a proxy of $\Delta \ln(TECH)$. Similarly, the change in the stock of human capital $\Delta \ln(HK)$ is proxied by continuous training ($TRAIN_{it}$). Firms' investments in training are indeed a flow which increments the stock of human capital.

Another issue raised by equations (2) is that of reverse causality. Our estimates may indeed capture the impact of changes in the age structure of the workforce on training and/or innovation rather than the opposite. This problem arises in particular if the age structure is persistent over time which is likely to be the case.[1] In order to overcome this problem, we control for the initial age structure of the workforce, $P_{a,i,t-1}$, i.e. the age structure before ICT and innovative work practices were introduced[2]. Moreover, we lag our explanatory variables one period[3] so that our model captures how *past* training (i.e. the change in the stock of human capital between *t-1* and *t*) and innovation (i.e. the change in the stock of technological and organisational capital) affect the *subsequent* change in the age structure of the workforce (between *t* and *t+1*), controlling for its initial value.[4]

In our data, the introduction of ICT and/or innovative work practices ($INNOV_{it}$) is measured between the beginning of 1995 and the end of 1997. So, we consider changes in the wage bill shares of the various age groups ($\Delta S_{a,i,t+1}$) over 1998-2000. Our training measure is averaged over 1995-1997 and we control for the age structure of the workforce as of 1994, i.e. before the introduction of any innovative device.

This specification aims at studying the impact of training investments – which may be specific to the various age groups – on the employment prospects of older workers and the role the former may play in mitigating the effects of innovation. Reverse causality problems as well as time-invariant heterogeneity are taken into account. Nonetheless, a causal interpretation of our estimates relies upon the assumption that training and innovations are

[1] In order to highlight this point, let's consider the extreme case in which there is no entry nor exit between the end of the 1980s and 1998 (the year that we consider – see below).The age structure of the workforce in 1998 would then be identical to that of 1988 with every employee being 10 years older. The theory of human capital accumulation over the life cycle (Ben Porath, 1967) as well as empirical evidence suggest that middle-aged workers receive a disproportionate amount of training. So, firms in which a large proportion of employees is aged 30 to 50 years old in 1988 will massively invest in training and will mechanically have a workforce aged 40 to 60 years old in 1998. This would result in a positive correlation between training in 1988 and the proportion of workers aged 40 to 60 in the workforce in 1998. But this correlation would not be due to the causal effect of training on maintaining senior workers in employment.

[2] More specifically, it is the share of the various age groups in the number of days worked as of 1994.

[3] We introduce time subscripts *t*, *t+1* and t-1 to make clear that variables are measured over different periods. However, the introduction of ICT and innovative work practices is only observed over one period; each firm enters the estimation only once (with some variables in 3-year difference).

[4] A potential drawback of this method is that if new ICT or innovative work practices have been introduced (between *t* and *t+1*), they do not show up in our data which may lead us to consider as non innovative firms that will become so a few years later. Note however that this should bias our results towards finding no impact of ICT and innovative work practices.

exogenous to future changes in the structure of the workforce. This assumption is common in the literature on technical and organisational change, given the lack of plausible instruments. It must however be kept in mind.

A problem with equations (3) is that the error terms $\varepsilon_{a,i}$ may be correlated across age groups within a given firm. So, in order to get an efficient estimator of the standard errors of the various coefficients, we need to take into account the shape of the variance-covariance matrix $\varepsilon_i = \{\varepsilon_{2,i},...,\varepsilon_{A,i}\}$. We do so by estimating a SUR model by joint generalised least squares (JGLS). When the explanatory variables are the same in all equations - as is the case here - this amounts to estimating the system by OLS equation by equation.[5]

Worker flows

Another way to get at the role of innovation and training in shaping the employment prospects of older workers is to estimate directly worker flows both into and out of firms as a function of past adoption of ICT and/or innovative work practices and past training investments. This allows us to identify the mechanisms through which innovation and training affect labour demand: is the main effect on hirings or alternatively on separations?

We denote $N_{a,i,t}^{HIRE}$ the number of workers aged *a* who are hired at year *t* in firm *i* and $N_{a,i,t}^{EXIT}$ the number of workers of the same age group who leave the firm in the course of the year.

We define the share of newly hired workers aged *a* in firm *i* at date *t* as $P_{a,i,t}^{HIRE} = \frac{N_{a,i,t}^{HIRE}}{N_{a,i,t}}$ and the share of workers leaving the firm as: $P_{a,i,t}^{EXIT} = \frac{N_{a,i,t}^{EXIT}}{N_{a,i,t}}$. We assume that $P_{a,i,t}^{HIRE}$ and $P_{a,i,t}^{EXIT}$ can be written as:

[5] See, e.g., Theorem 7.6 in Wooldridge, 2002.

$$P_{a,i,t}^{HIRE} = \alpha_a^{HIRE} + \beta_{a,INNOV}^{HIRE} INNOV_{i,t-1} + \beta_{a,TRAIN}^{HIRE} TRAIN_{i,t-1} + \beta_{a,K}^{HIRE} \Delta\ln(K)_{i,t}$$

$$+\beta_{a,VA}^{HIRE} \Delta\ln(VA)_{i,t} + \sum_{a\in\{2...A\}} \beta_{a,a'}^{HIRE} \Delta\ln(W_a / W_1)_{i,t} + \sum_{a\in\{2...A\}} \beta_a^{HIRE} .P_{a,i,t-1} + \beta_{a,M}^{HIRE} .M_{a,i,t} + \varepsilon_{a,i,t}^{HIRE}$$

(4)

and

$$P_{a,i,t}^{EXIT} = \alpha_a^{EXIT} + \beta_{a,INNOV}^{EXIT} INNOV_{i,t-1} + \beta_{a,TRAIN}^{EXIT} TRAIN_{i,t-1} + \beta_{a,K}^{EXIT} \Delta\ln(K)_{i,t}$$

$$+\beta_{a,VA}^{EXIT} \Delta\ln(VA)_{i,t} + \sum_{a\in\{2...A\}} \beta_{a,a'}^{EXIT} \Delta\ln(W_a / W_1)_{i,t} + \sum_{a\in\{2...A\}} \beta_a^{EXIT} .P_{a,i,t-1} + \beta_{a,M}^{EXIT} .M_{a,i,t} + \varepsilon_{a,i,t}^{EXIT}$$

(5)

$INNOV_{i,t-1}$ denotes our measure of innovation and $TRAIN_{i,t-1}$, the investment in training which are both measured over 1995-1997. $\{ \Delta\ln(W_a / W_1)_{i,t} \; ; \; \Delta\ln(K)_{i,t} \; ; \; \Delta\ln(VA)_{i,t} \}$ is a vector of demand factors (change in relative wages, in physical capital and in value-added between 1998 and 2000) specific to firm *i*. $P_{a,i,t-1}$ is the share of age group *a* in the workforce before the introduction of innovation (i.e. as of 1994) and M_{it} is a vector of controls identical to X_{it} in equation (3) but including year fixed effects for 1999 and 2000.[6] $\varepsilon_{a,i,t-1}^{HIRE}$ and $\varepsilon_{a,i,t-1}^{EXIT}$ are stochastic error terms.

The main advantage of this linear model is that it allows us to estimate the share of inflows and outflows for all age groups simultaneously by using the SUR method – see section 2.1 above. In turn, this allows us to take into account the potential correlation between hirings and separations across various age groups.

Given that we are interested in the impact of innovation and training upon hirings and

[6] We include time dummies because our observations are pooled together for years 1998, 1999 and 2000 – see Data section below.

separations of older workers *relative* to younger ones, we decompose $\beta_{a,INNOV}^{HIRE}$ and $\beta_{a,TRAIN}^{HIRE}$ (resp. $\beta_{a,INNOV}^{EXIT}$ and $\beta_{a,TRAIN}^{EXIT}$) into two different terms: θ^{HIRE} (resp. θ^{EXIT}) is a component that is common to all age groups and represents the average impact of innovation or training on hiring (resp. on separations) and θ_{a}^{HIRE} (resp. θ_{a}^{EXIT}) is a component which is age specific:

$$\beta_{a}^{HIRE} = \theta^{HIRE} + \theta_{a}^{HIRE} \text{ and } \beta_{a}^{EXIT} = \theta^{EXIT} + \theta_{a}^{EXIT}$$

In order to be able to identify the model, we constrain the θ_{a}^{HIRE} (resp. θ_{a}^{EXIT}) to add up to zero. As a consequence:

$$\theta^{HIRE} = \frac{\sum \beta_{a}^{HIRE}}{A} \text{ et } \theta_{a}^{HIRE} = \beta_{a}^{HIRE} - \frac{\sum \beta_{a}^{HIRE}}{A} \qquad (6)$$

The same holds for separations. The corresponding standard errors account for the estimated covariances between the β_{a}^{HIRE}'s.

II. THE DATA

The data that we use come from several sources. Information on ICT and innovative work practices comes from the COI survey (Changements Organisationnels et Informatisation) carried out by SESSI[7] at the end of 1997 and covering 4,283 firms with more than 20 workers in the manufacturing sector.[8] In order to get information on wages and on the age structure of the workforce, we matched COI with mandatory social security reports: the DADS files (Déclarations Annuelles des Données Sociales). The DADS is an exhaustive dataset providing information on firm size and industry on a yearly basis since 1994. Moreover, for each employee, the DADS has information on the number of hours and days worked during the

[7] French Ministry of Industry.
[8] Complementary surveys have been conducted in the food-processing, trade and service sectors, but the number of firms covered by each of them is much smaller than in the manufacturing sector (resp. 970, 648 and 1482). Moreover, the questions asked being somewhat different, we will focus exclusively on the manufacturing sector.

year, as well as on wages, age and occupation. Information on physical capital and value-added comes from the BRN (Bénéfices Réels et Normaux) which consists of firms' balance sheets collected by the tax administration. It contains more than 600,000 firms from the private non-financial sector and covers about 80% of total sales in the French economy.

Training data are retrieved from the "24-83" fiscal records. They contain information on the number of workers receiving training and the volume of training hours broken down by gender, age and occupation for every year. The "24-83" records are exhaustive for all French firms with more than 10 employees, but only a sample is available for research. This sample contains 15 to 20,000 firms every year but a larger sample (30 to 40,000 firms) is available every three years.

Matching the different databases leaves us with a sample of 2,352 firms as compared to 4,283 in the original COI dataset. This is due to the fact that we only keep those firms for which we have data on training while the "24-83" records are not exhaustive. The firms that we lose are essentially small ones since the first decile of the size distribution has less than 26 workers in the original dataset as compared to 34 in ours. Similarly, the median size of firms in our sample is 150 workers as compared to 86 in the COI database and the average size is 552 as compared to 429 in COI. Nonetheless, the distribution of firms across industries is very similar in both datasets: about half of the firms belong to the intermediate good sector - 48.1% in our sample as compared to 45.2% in COI (see Appendix Table A.1) - and almost one fourth is in the durable good sector – 23.6% in COI as compared to 23.4% in our sample. The only notable difference lies in the share of firms in the motor vehicle manufacturing industry - with 4.6% in our sample as compared to 3.7% in COI – and to a smaller extent in the non-durable good sector – 21.3% in our database as compared to 25.1% in COI. But overall, differences between both datasets remain very limited.

As regards worker flows, we allow adjustment to take time and thus pool our data over 1998-

2000. We jointly estimate employment flows for all groups in each firm. So we use a sample of 6,824 firms * year; for each of these, we measure inflows and outflows by age groups.

The age groups that we consider are 20 to 29, 30 to 39, 40 to 49 and 50 to 59 years old. Employees aged 60 and more are excluded given that the legal age of retirement was 60 during the period under study.

Using the information available in the COI dataset, we define 4 indicators of introduction of new technologies and innovative work practices. Following Biscourp et al. (2002), our first indicator is *Internet* which takes value 1 if the firm uses this technology either for emailing or to diffuse or gather information; it takes value 0 otherwise. We assume that Internet being at its very start in France in the mid-1990s, the rate of use declared in 1997 is equivalent to an adoption rate. Our second indicator is D_COMP, which captures the introduction of network-interconnected computers in the production department. D_COMP is equal to 1 if the firm has introduced this type of equipment between 1995 and 1997; 0 otherwise. The COI survey also has information on the introduction of innovative work practices. A first indicator captures the reduction in hierarchical layers within firms: D_HIERAR is equal to 1 if the number of hierarchical layers was smaller in 1997 than in 1995; 0 otherwise. A second indicator captures the increase in the amount of responsibility awarded to operators over the period: D_RESP varies between -10 and +10 according to the number of new responsibilities operators have been awarded between 1995 and 1997[9]. These two variables are not strictly orthogonal since they both capture a specific dimension of the decentralisation process that took place in many firms in the 1990s. However, they are far from being identical; in our sample, the coefficient

[9] The question is phrased as follows: "In the workshops of your firm, who is entitled to: (1) fine-tune the apparels (2) operate basic maintenance (3) allocate tasks among operators (4) control the quality of supplies (5) control the quality of the product (6) participate to performance improvement (7) participate to project-management teams (8) stop the production process in case of incident (9) make a first diagnosis in case of incident (10) start production again when stopped because of incident". For each question, the survey offers three possible answers: "hierarchy, operator, specialist". The questions are asked for 1994 and 1997. We give value 1 to each answer involving an operator so that the aggregate responsibility indicator varies between 0 and 10. Our D_RESP variable is then defined as the difference between the aggregate indicators for 1997 and 1994.

of correlation between both variables is 0.39. The reduction in the number of hierarchical layers generates a flattening of the organisation and increases horizontal communication across workers (or groups of workers) at the expense of direct reporting to the hierarchy. In contrast, the increase in the amount of responsibility awarded to operators enlarges the scope of their intervention thereby increasing their level of autonomy. Both types of changes are not necessarily adopted together: firms may increase the autonomy and responsibility of workers to foster the reactivity of the production process, while maintaining a strong vertical structure in order to avoid agency problems. Symmetrically, firms may flatten their organisation while maintaining a key role for specialists as regards maintenance and quality controls, for example.

As regards training, the "24-83" records provide information on the relative access rate to training for three different age groups: younger than 25 years old, 25 to 44 years old and 45 and older. More precisely, for each of the above age groups, we build a variable denoted TRAIN_X which is equal to the rate of training in age group X divided by the average rate of training in the workforce.[10] This variable captures the relative rate of training across the various age groups.[11] To the extent that our data come from different sources, the age groups used to build the relative training rates – younger than 25 years old, 25-44 years old and 45 years old and above – do not exactly correspond to the ones we use to capture the change in the age structure of the workforce. For the sake of coherence with our technical and organisational change indicators, the training variables are averaged over 1995-1997 – see descriptive statistics in Appendix Tables A2 to A5.

[10] TRAIN_X = [(number of employees from age group X receiving training) / number of employees in age group X)] / [(total number of trainees in the firm / total number of employees in the firm)].
[11] The relative rates of training for the three age groups are not strictly collinear as long as the age groups do not have the same size.

III. Results

Innovation, training and change in the age structure of the workforce

Overall effects

As a first step, we estimate the impact of the adoption of ICT, innovative work practices and training on the subsequent change in the age structure of the workforce, controlling for the initial age structure to the extent that it generates a mechanical change in the wage bill shares of the various age groups (see Table 1).[12]

Consistent to what is found in the literature, ICT and innovative work practices appear to be age biased: both the introduction of the Internet and the adoption of network-interconnected computers are correlated with an increase in the share of workers aged 30-39 in the wage bill, whereas they are associated with a decrease in the share of workers aged 50-59. The introduction of innovative work practices also affects the wage bill share of the various age groups. As for ICT, an increase in the amount of responsibility awarded to operators is associated with an increase in the share of younger workers (30 to 39) in the wage bill and with a reduction in the share of older workers (aged 50-59). Interestingly, a reduction in the number of hierarchical layers seems to have the opposite effect: it is correlated with an increase in the share of workers aged 50-59 and with a reduction in the share of younger employees (aged 30-39).[13] This result suggests that the decentralisation of the production process associated with the reduction in the number of hierarchical layers may generate some form of return to experience which positively affects the employment and/or wage prospects

[12] All our regressions also control for average training expenditures over 1995-1997. By so doing, we control for potential differences in training investments across firms. This is necessary in order to make sure that the impact of training on the age structure of the workforce only goes through the relative access rate of the various age groups.

[13] Despite the fact that D_HIERAR and D_RESP are not perfectly correlated (see Section 3), one could worry that the different sign on their coefficients could be due to collinearity problems. We check this by removing successively each variable from the regression: the sign of the coefficient on the remaining regressor remains unchanged. The magnitude of the effect tends to go down and becomes insignificant in a number of cases, which is not surprising given that both variables impact the age structure of the workforce in an opposite way.

of older workers.

As regards the impact of training, the results presented in Table 1 suggest that training of older workers (TRAIN_3) is associated with a subsequent increase in the share of the wage bill accruing to them. The higher the relative training rate of workers aged 45 and above as compared to average training in the firm in 1995-1997, the greater the increase in their wage bill share over 1998-2000, all other things equal. In contrast, training of older workers has a negative impact on the change in the wage bill share of workers aged 30-39. Interestingly, there is no similar effect of the relative training rates of younger age groups: TRAIN_1 and TRAIN_2 are not significantly correlated to changes in the wage bill share of the corresponding age groups.

The model we have estimated so far was derived from a translog cost function so that we have focused on changes in the *wage bill* shares. However, one may wonder whether the observed correlations are due to changes in the share of the various age groups in employment or, alternatively, to changes in relative wages. In order to tackle this issue, we re-estimate equation (3) on the shares of the 4 age groups in employment – more precisely, in the number of days worked. The corresponding results are presented in Table 2. The coefficients on the innovation variables are close to those obtained in Table 1, but some of them are less precisely estimated. The Internet is still biased against older workers but the positive correlation with the share of workers aged 30-39 in employment is not significant. Symmetrically, the introduction of network-interconnected computers and the increase in the amount of responsibility awarded to operators are still positively associated with the share of younger workers (aged 30-39) but the negative correlation with the share of older workers is no longer significant. By contrast, the decrease in the number of hierarchical layers has the same effect on employment as on wage bill shares: it is positive for older workers and negative for younger ones. As regards training, it does not affect the age structure of employment when focused on young and middle-aged workers. As was the case for the wage bill shares, the only significant results are for the relative training rate of older workers which negatively affects the share of workers aged 30-39 in employment but positively affects that of workers aged 40-49, while it has no effect on the oldest age group – whereas the opposite held in Table 1. Overall, the results we obtained on wage bill shares seem to be largely driven by effects on the age structure of employment, but in some cases relative wages play a role too. Regarding the introduction of network-interconnected computers and the increase in the amount of responsibility awarded to operators, the negative correlation with the wage bill share of older workers evidenced in Table 1 seems to be mostly due to a decrease in their relative wage, rather than to a decrease in their share in employment.[14] Similarly, the positive impact of the relative rate of training of older workers on the subsequent change in their wage bill share would essentially go through an impact on the relative wages of older workers, rather than an increase in their share in total employment.

Overall, our results suggest that technological and organisational innovations are biased against older workers and in favour of younger ones. In contrast, access to training for workers aged 45 and more seems to have a positive impact on their employment and wage prospects: on their share in employment for those aged 40 to 49 and on their relative wage for the oldest group (aged 50-59).

Innovation, training and change in the age structure within occupations

The relationships between innovation, training and change in the age structure of the workforce are confirmed when re-estimating our model within occupational categories (see Table 3).

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[14] For instance, the coefficient on the introduction of network-interconnected computers is -.44 (significant at the 10% level) when considering the wage bill share of workers aged 50 to 59 as the dependent variable, and only -.16 (not statistically significant) when considering their share in employment. Note however that standard errors are large, so that the difference in point estimates is only suggestive, but not statistically significant.

Regarding innovation, the age bias is particularly strong within the managerial group. The Internet positively affects the wage bill share of managers aged 30-39 while it is negatively correlated with that of older managers. Similarly, the introduction of network-interconnected computers and the increase in the amount of responsibility awarded to operators appear to be negatively correlated with the wage bill share of older managers. These effects are far less stark for clerks since only the Internet has any significant effect. However, the correlation between its adoption and the wage bill share of the various age groups appears to be negative for the 30-39 year olds which does not support the age bias hypothesis. In contrast, the adoption of the Internet is associated with a decrease in the proportion of older blue-collars. Interestingly, the positive correlation between the reduction in the number of hierarchical layers and the wage bill share of older workers found in Table 1 seems to be almost entirely due to managers. This "pro-age" bias does not exist for clerks and even seems to change sign for blue-collars: the flattening of the hierarchical structure is indeed associated with an increase in the share of the youngest age group (20-29 years old) at the expense of the 30-39 year olds. One of the reasons of the pro-age bias associated with the reduction in hierarchical layers within the managerial group may have to do with a composition effect. Middle managers are indeed particularly affected by delayering. Since they are likely to be younger than top managers, the age structure of the managerial group is likely to shift towards older ages as a consequence of delayering. Another potential explanation is that experience and initial skills are complements so that the former becomes an asset when the hierarchical structure flattens, but only for the most highly skilled workers.

Regarding training, the relationship between the relative training rate of older workers and their share in the wage bill is less stark within occupations. This may be due to the shortcomings of our data. Ideally, we would have correlated the relative rate of training of the various age groups of *managers* with the change in the age structure of the workforce among *managers*; and similarly for clerks and blue-collars. However, our training data do not include information on training rates by age *and* occupation. So, we can only correlate the relative training rate in each age group – as computed for *all occupations* - with the change in the age structure of the workforce within our three occupational categories. This imperfect correspondence may result in an attenuation bias. In our view, such an exercise is however interesting in order to detect which occupations are most sensitive to changes in relative training rates. As indicated by results in Table 3, the relative training rate of workers aged 45 and above is still positively correlated to an increase in their wage bill share, but the coefficient is only significant for clerks (and at the 10% level).[15] However, training of older workers is persistently associated with a decrease in the wage bill share of younger age groups: this is the case for workers aged 20-29 in managerial occupations and for workers aged 30-39 among blue-collars. Overall, greater access to training for older workers between 1995 and 1997 is associated with a change in the age structure of the workforce at the expense of younger workers, and in favour of older ones in the next period (1998-2000). A similar result is obtained for middle-aged workers (25-44 years old): among clerks, the relative training rate of workers aged 25-44 is negatively correlated to the change in the wage bill share of the youngest age group (20-29 years old) and positively correlated with the share of workers who are directly affected by the training (at least for those aged 40-49). Moreover, training of middle-aged clerks is negatively associated with the change in the wage bill share of the oldest age group within the clerk category (50-59 years old). These results are not surprising given the definition of our training indicators: if middle-aged workers have been trained more than average over the 1995-1997 period, this means that older and/or younger workers have been trained less. So, the decrease in their wage bill share over the next period just confirms the existence of a relationship between training and change in the age structure

[15] The fact that the estimates are less often statistically significant may be due in principle to reduced precision at this disaggregated level. However, point estimates also tend to be lower.

of the workforce in favour of those age groups who have been directly affected by training. However, this result does not hold for blue-collars: training of workers aged 25-44 is indeed associated with an increase in the wage bill share of older workers (aged 50-59) and with a decrease in that of workers aged 40-49. Finally, the relative training rate of the youngest age group (less than 25 years old) is not significantly correlated to any change in the age structure of the workforce.

Overall, the age bias of ICT and innovative work practices seems to be particularly strong among managers. Training of older workers positively affects their wage and/or employment prospects, but the effect is significant only among clerks.

Training, innovation and the age bias of ICT and innovative work practices

One important issue we want to tackle here is whether training may mitigate the age bias induced by ICT and innovative work practices. In order to answer this question, we estimate a specification , similar to that used in Table 1, in which we interact the relative rate of training of older workers with our innovation variables – see Table 4. The coefficients on the interaction terms are not very encouraging. While the Internet does not seem to have much effect on the wage bill shares of the various age groups per se, the correlation becomes positive for the youngest age group (20-29 years old) and negative for workers aged 40-49 when introduced in firms which invest in training in a disproportionate way for older workers. Similarly, while the flattening of the hierarchical structure seems to have a negative effect on workers in their 30s per se, this effect vanishes in firms where older workers receive more training than average. The only case in which training of older workers seems to dampen the age bias due to innovation is for responsibilities awarded to operators: while the direct effect of this new organisational practice is negative for the wage bill share of the oldest age group, it is strongly attenuated when older workers have been trained more than average in the previous period.

Overall, technological and organisational innovations on the one hand and training on the other hand seem to have opposite effects on the age structure of the workforce – except for the flattening of the hierarchical structure. However, our results do not provide evidence that training would reduce the age bias due to the introduction of ICT and innovative work practices.

4.2 Innovation, training and employment flows by age group

The results presented in Table 5 analyse inflows and outflows of workers both on average and for each age group. These flows relate to all types of labour contracts, be they permanent or temporary.

The impact of ICT and innovative work practices on the age structure of employment inflows and outflows appears to be quite varied according to the type of innovation under study. The adoption of the Internet increases hirings without affecting separations, whereas the introduction of network-interconnected computers and the reduction in the number of hierarchical layers do not seem to affect the aggregate level of inflows and outflows. As regards the increase in the amount of responsibility awarded to operators, it contributes to reduce turnover as a whole given its negative effect on both hirings and separations. The same holds for training of younger and middle-aged workers which is negatively correlated both with inflows and outflows. As regards the relative rate of training of older workers, it is also associated with a reduction in inflows, but does not seem to be significantly correlated with outflows.

Coming now to the differential impact on the inflows and outflows of the various age groups, younger workers appear to be positively affected by the Internet: it increases hirings of workers aged 20-29 more than average while reducing their outflow. The opposite holds for older age groups since the Internet is associated with an increase in outflows (with no increase in inflows) for workers aged 30-39 and to a reduction in relative hirings (with no impact on separations) for workers aged 40-49. The introduction of network-interconnected computers reduces hirings in a significant way in the youngest age group, but it also reduces separations. The opposite holds for workers aged 50-59 for whom outflows increase when network-interconnected computers are introduced. The reduction in the number of hierarchical layers increases inflows of workers aged 20-29 and reduces those of workers aged 30-39 whereas it does not seem to affect the age structure of outflows. In contrast, increasing responsibility of operators has no impact on the age structure of inflows, whereas it has a clear negative effect on older workers as far as separations are concerned: D_RESP reduces outflows less than average for workers aged 40-49 and 50-59 while it reduces separations more than average in the youngest age group.

As regards training investments made by firms, they strongly affect hirings and separations of the age groups which are directly affected by the training. The relative rate of training of workers aged 25 years old and below reduces outflows more than average in the corresponding age group (i.e. workers aged 20-29), without affecting inflows. In parallel it negatively affects the oldest workers by reducing their inflows more than their outflows. Regarding training of middle-aged workers (25-44 years old) it reduces outflows in the 30-39 age group more than average as well as the rate of turnover of workers aged 40-49. In contrast, it negatively affects older workers as compared to younger age groups, to the extent that it reduces their outflows much less than for middle-aged workers. Finally, training of older workers tends to protect them. It reduces inflows of all categories of workers but this reduction is smaller than average for workers aged 50-59, whereas it is significantly larger than average for competing age groups (in particular those aged 40-49). As a consequence, training older workers more than average has a positive impact on their relative share in employment.

Overall, it seems that a large part of the effect of innovation and training on workers' flows by age group goes through turnover. The adoption of network-interconnected computers reduces the rate of turnover among the youngest age group. Training of middle-aged and older workers contributes to the reduction of the rate of turnover among the 40-49 year old group. Moreover, when innovations and training only affect hirings or separations, our results suggest that ICT and innovative work practices have a negative impact on older workers as compared to other age groups. This occurs either because innovations raise the inflow of older workers less than average (e.g. Internet for the 40-49) or because they increase their outflows relative to other age groups (e.g. network-interconnected computers and increase in the responsibility of operators for employees aged 50 and above). In contrast, training seems to protect the categories of workers who are directly affected, either by increasing their hirings as compared to the other age groups – as is the case for older workers – or by reducing their separations - as is the case for the youngest group and for middle-aged workers.

All in all, the analysis of employment flows confirms the results obtained when estimating the wage bill share model: ICT and innovative work practices negatively affect the employment prospects of older workers, whereas concentrating training investments on them helps stabilise their share in the wage bill in the next period.

5. Conclusion

Our research confirms that ICT and innovative work practices are biased against older workers. This is the way we interpret the negative correlation that we find between technological and organisational innovations on the one hand and subsequent change in the wage bill share of older workers on the other hand. This results holds with various measures of technological and organisational change, namely the introduction of the Internet, the introduction of network-interconnected computers and the increase in the amount of responsibility awarded to operators: all three innovative devices increase the share of workers in their 30s and reduce that of older workers in the wage bill and, to a smaller extent, in employment. Interestingly, in contrast, the flattening of the hierarchical structure appears to be favourable to older workers – and correspondingly unfavourable to workers aged 30-39: it increases the share of workers aged 50-59 both in the wage bill and in employment. One reason for this may be that tacit knowledge plays an important role when flattening the hierarchical structure. Skills acquired by older workers through learning-by-doing are all the more necessary to firms that they incorporate an important part of tacit knowledge which is hardly substitutable. When this is the case, older workers possess a valuable asset which may enhance their employability. When flattening the hierarchical structure of the firm, tacit knowledge held by workers is likely to become more important, in particular as regards communication and work organisation. Older workers then benefit from a comparative advantage which does not exist when technological and organisational innovations generate greater knowledge codification. Such a mechanism could account for the positive impact of the reduction in hierarchical layers upon the employment prospects of older workers.

Moreover, our results suggest that training tends to protect older workers in terms of employment and/or earnings. The relative training rate of workers aged 45 and above is indeed associated with an increase in their share in employment (for those aged 40-49) or in the wage bill (for the 50-59 age group). Thus doing, it contributes to offset the negative effects of ICT and innovative work practices on older workers. However, let us underline that training does not reduce the age bias associated with technological and/or organisational innovations to the extent that the interaction terms between innovations and training are either insignificant or negative in the models that we estimate. So, although training has a positive impact on employment and earnings of older workers, it offers only limited prospects to enhance their employability, in a context where technological and organisational innovations tend to develop.

These results are obtained by estimating changes in the wage bill and employment shares of the various age groups. We get very similar patterns when estimating employment flows. Our results suggest that technological and organisational innovations have mostly negative effects on older workers in relative terms, either because they raise hirings less than average or because they increase separations in a disproportionate way in the oldest age group. In contrast, training investments reduce turnover but also protect those groups of workers who are directly affected by the training, either by increasing hirings as compared to other age groups – as is the case for older workers – or by reducing separations – as happens for younger or middle-aged workers.

Our research suggests that policies aiming at increasing the employability of older workers cannot entirely rely on training in a world where technological and organisational innovations are expanding. More has to be done in order to help older workers adapt to the new communication and organisational devices. One option probably consists in awarding workers more time to adjust to the new production methods – see Jolivet (2003). This is of course a challenge in a context of increasing competition and globalisation of economic activities. However, given the rhythm at which population is ageing in most developed countries, this challenge has to be met in order to maintain older workers in employment.

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