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Abstract

This paper investigates the relationships between new technologies, innovative workplace practices and the age structure of the workforce in a sample of French manufacturing firms. We find evidence that the wage bill share of older workers is lower in innovative firms and that the opposite holds for younger workers. This age bias is also evidenced within occupational groups, thus suggesting that skills do not completely protect workers against the labour market consequences of ageing. More detailed analysis of employment inflows and outflows shows that new technologies essentially affect older workers through reduced hiring opportunities, whereas organisational innovations mainly increase their probability of exit. This suggests that some skill obsolescence may be at work in our sample.

Keywords: new work practices, technology, older workers, labour demand

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Nouvelles technologies, changements organisationnels et gestion des âges dans les entreprises

Résumé

Cette étude s'intéresse aux relations entre nouvelles technologies, changements organisationnels et structure par âge de l'emploi dans un échantillon d'entreprises industrielles. Nous trouvons que les salariés âgés représentent une part plus faible de la masse salariale dans les entreprises les plus innovantes. Ce "biais contre l'âge" est vérifié également au sein des différentes qualifications : la qualification ne suffirait donc pas à protéger complètement contre les conséquences de l'âge en termes d'employabilité. Nous complétons l'analyse en nous intéressant aux flux d'emploi : les nouvelles technologies affectent l'emploi des salariés âgés via des embauches moins nombreuses, alors que les changements organisationnels se traduisent surtout par des sorties plus nombreuses. Ces observations suggèrent l'existence d'une obsolescence des qualifications.

Mots-clés : changements technologiques, changements organisationnels, demande de travail

Classification JEL : J23, L23, O33

1 Introduction

In response to increasing national and international competition, many American and European firms have intensified their use of new technologies and reorganised their workplace in order to introduce more flexible organisational devices. These include self-managed teams, multi-tasking, just-in-time, total quality management and some decentralisation of decision making. They are often referred to as ”high performance” workplace practices.

Evidence in the literature suggests that both technological and organisational innovations are skill biased. As regards technological change, there is a general agreement that the development of new information and communication technologies has hurt the employment prospects of less skilled workers (see Chennells and Van Reenen (2002) for a review). The literature on organisational change is more recent, but several works suggest that innovative workplace practices have also been detrimental to lower skilled employment in various countries (see Caroli and Van Reenen (2001) for France and the UK, Bresnahan et al (2002) for the USA and Bauer and Bender (2004) for Germany).

One related issue we tackle here is: are new technologies and workplace practices biased against age? In other words, do they hurt the employment prospects of older workers, respective to younger ones? This question is of particular relevance in Europe given the demographic and activity patterns of the population.

The total population of the EU15 is ageing fast. In the short run, the proportion of people aged 55-64 is forecasted to rise by about 1.4% per year between 2002 and 2010 (European Commission, 2003). At the same time, the number of workers going into retirement will increase sharply due to the baby-boom generation reaching retirement age. As a consequence, the cost of financing pension schemes will increase sharply. This is of particular concern given the low level of the employment rate of older workers: no more than 40% of the population aged 55-64 is employed in Europe, as compared to 58% in the USA and 62% in Japan. From a policy point of view, the extent of the problem is such that, in 2001, the European Council has set up the so-called ”Stockholm target”, aiming to increase the employment rate of workers aged 55-64 to 50% by 2010.

In analysing the reasons for the low employment rate of older workers, the supply side dimension has long been put forward (Gruber and Wise, 2004). However, one can wonder whether demand side considerations could also be at play, in particular in a context of rapid technical and organisational changes. The relationship between innovation and the age structure of the workforce is, a priori, uncertain. On the one hand, innovation may be positive for older workers because they are more skilled and experienced. Given that innovation is skill biased, one could expect new technologies and workplace practices to be favourable to older workers. On the other hand, innovation may negatively affect older workers if it accelerates skill obsolescence, i.e. if it reduces the market value of their skills. Since Rosen (1975), the idea that technological innovation may raise skill obsolescence has been tested in various ways in the literature. A first strand of papers check whether older workers have difficulty using computers. In general, evidence of such difficulty is not compelling. Borghans and Ter Weel (2002) find virtually no impact of age on individual computer use once controlling for tasks. Correspondingly, they find no significant relationship between computer use and the share of older workers in employment in various occupational groups. Friedberg (2003) finds partial evidence of skill obsolescence. Recent technological change in a worker's environment appears to have a negative impact on individual computer use, but only for workers close to retirement. According to Friedberg, this shows that impending retirement reduces the value of acquiring new computer skills thus leading less skilled workers to retire earlier. Additional work suggests that, if any, skill obsolescence is stronger for higher educated workers. Neuman and Weiss (1995) find that earnings peak earlier for high educated workers in the high-tech sector. Similarly, Weinberg (2002) displays that computer use peaks for low levels of seniority for college graduates and that the opposite holds for high-school graduates.

From this first group of studies, older workers do not appear to lag behind systematically in terms of computer use. One problem in this literature is, of course, selection bias. The probability of using a computer is measured on a sample of workers who all are in employment. However, it is quite likely that workers who are still employed when they get old are the most efficient and that this correlates with computer use. If this is the case, the impact of age as estimated in this literature will be underestimated, given that most unable workers will have already retired or been laid-off.

A second empirical strategy has therefore consisted in estimating the impact of computer use on retirement decisions. Bartel and Sicherman (1993) show that workers in industries with a higher average rate of technical change[1] tend to retire later. However, unexpected changes in the rate of technical change[2] induce workers to retire earlier. This suggests that, when introduced, technological innovations generate some skills obsolescence. In the longer run though, technical change makes retraining more profitable which, in turn, creates an incentive for workers in high-tech industries to retire later.

Another possible impact of new technologies and organisational practices has to do with the employment prospects of older workers. In order to tackle this issue, one should use firm or establishment-level data and investigate how labour demand varies according to age and to firms' innovativeness. To our knowledge, only one paper, by Heywood et al. (1999), indirectly addresses this issue. Using establishment-level data from Hong-Kong, the authors study the determinants of the share of older workers among recently hired employees. They find a negative correlation with a number of indicators of back-loaded compensation but no significant effect of technical change. One limitation of this paper is that its definition of older workers is very large, including all employees aged 35 and above. Moreover, the authors

[1]The average rate of technical change is measured by ten year differences in the average annual rate of TFP growth.

[2]Unexpected changes are measured as the deviation from the permanent rate of technical change divided by the standard deviation over the past 10 years.

are mainly concerned with the impact of compensation packages characteristics. So technical change is introduced as a mere control and innovative workplace practices are not considered. The current paper plans to contribute to the empirical literature by explicitely studying the impact of technnological and organisational innovations upon the age structure of the workforce at the firm level.

We provide empirical evidence regarding the relationships between new technologies, innovative workplace practices and the age structure of the workforce. Using firm-level data for France in the 1990s, we investigate how the use of innovative devices affects the wage bill share of various age groups within firms. We find evidence that the the wage bill share of older workers is lower in innovative firms and that the opposite holds for younger workers. This pattern of results also holds within occupational groups, thus suggesting that skills do not completely protect older workers against the labour market effects of innovation. This anti-age bias of innovative firms is consistent with the general pattern of employment inflows and outflows. We find that new technologies enhance hiring opportunities for younger workers while they reduce them for older ones. In contrast, the impact of organisational innovation is through exits: it raises them in the older age groups while decreasing them for younger workers. This overall pattern of results suggests that skill obsolescence may be one reason for the anti-age bias of innovative firms.

The paper is organised as follows. Section 2. outlines the econometric model. Section 3. discusses the data. Results are presented in Section 4. Some concluding comments are offered in Section 5.

2 The Econometric Model

2.1 Wage bill shares

To investigate the relationships between new technologies, innovative workplace practices and the age structure of the workforce, we start from a classical labour demand framework, assuming that the cost function is a restricted translog (for instance, see Caroli and Van Reenen, 2001). Since we are interested in age effects, the only variable inputs are different types of labour indexed by age a. Under these assumptions, it is straightforward to derive a system of wage bill share equations for each age category a of the familiar form:

$$\begin{aligned} S^*_{a,i,t} &= \alpha_a + \sum_{a' \in \{1,\ldots,A\}} \gamma_{a,a'}.\ln(W_{a'})_{i,t} + \gamma_{a,INNOV}.\ln(K^{INNOV})_{i,t} \\ &\quad + \gamma_{a,K}.\ln(K)_{i,t} + \gamma_{a,VA}.\ln(VA)_{i,t} + \psi_{a,i,t}. \end{aligned} \tag{1}$$

where $S^*_{a,i,t}$ is the static equilibrium wage bill share of age category a in firm i at time t, K the stock of tangible capital (assumed to be a quasi-fixed factor), VA the value-added of the firm, $W_{a'}$ the wage rates of workers of age category a' and $\psi_{a,i,t}$ stochastic error terms. We also assume that there is an other quasi-fixed factor, K^{INNOV}, that captures the use of new technologies and high-performance workplace practices in firms (see Section 3). The total number of age categories is A.

Since we consider the system of wage bill share equations for all age categories, we need to place further restrictions on the parameters. *Symmetry* implies that $\gamma_{a,a'} = \gamma_{a',a}$ for all a and a'. *Homogeneity* implies that we also have $\sum_{a=1,\ldots,A} \alpha_a = 1$ and $\sum_{a=1,\ldots,A} \gamma_{a,j} = 0$ for all j in $J = \{a = 1,\ldots,A; K; VA;\ K^{INNOV}\}$. Coupled with the fact that the shares add up to unity, one equation becomes redundant and we need only estimate the system for all age categories a but the first one. Our econometric model hence writes:

$$\begin{aligned} S^*_{a,i,t} &= \alpha_a + \sum_{a' \in \{2,\ldots,A\}} \gamma_{a,a'}.\ln(W_{a'}/W_1)_{i,t} + \gamma_{a,INNOV}.\ln(K^{INNOV})_{i,t} \\ &\quad + \gamma_{a,K}.\ln(K)_{i,t} + \gamma_{a,VA}.\ln(VA)_{i,t} + \psi_{a,i,t} \qquad \forall a \in \{2,\ldots,A\}. \end{aligned} \tag{2}$$

One problem with equation (2) is that error terms $\psi_{a,i,t}$ may be correlated for different age categories within the same firm at the same period of time. Therefore, in a standard regression, the shape of the covariance matrix of the $\psi_{i,t} = (\psi_{2,i,t},\ldots,\psi_{A,i,t})$ vector has to be taken into account in order to improve the efficiency of the estimation. This can be performed by using a joint generalized least square (JGLS) estimator. In the present case, we first perform an OLS regression and use the residuals to estimate the cross-equation covariance matrix used in the second step.

A second problem has to do with unobserved heterogeneity. A usual way to tackle the fixed effects problem is to estimate the model in long differences. However we cannot do so because our data has information on “innovativeness” (the

K^{INNOV} variable) at only one year (see Section 3). An alternative strategy to deal with this problem would be to use an instrumental variable technique to estimate equation (2). We did so in a previous version of the paper[3], using the first differences in our variables - computed over the three years prior to the survey - in order to instrument the static labour demand equation in a GMM estimation. These instruments proved very weak thus generating a massive bias in the GMM estimates. In the absence of better instruments, we opt for estimating the labour demand equations by JGLS and interpret the results as describing correlations rather than causality links.

2.2 Employment inflows and outflows

Wage bill share equations provide an insight of how the age structure of the labour force varies across innovative and non innovative firms. As a second step, we focus on inflows and outflows in order to determine whether the low demand for some age groups in innovative firms results in more separations or in reduced hiring opportunities.

Let $N^{HIRE}_{a,i,t}$ denote the number of newly hired workers of age a in firm i at time t, and $N^{EXIT}_{a,i,t}$ the number of workers aged a leaving[4] firm i at year t. We define the share of entrants aged a in firm i at year t as $P^{HIRE}_{a,i,t} = \frac{N^{HIRE}_{a,i,t}}{N_{a,i,t}}$ and the share of workers leaving the firm as $P^{EXIT}_{a,i,t} = \frac{N^{EXIT}_{a,i,t}}{N_{a,i,t}}$. We assume that $P^{EXIT}_{a,i,t}$ and $P^{HIRE}_{a,i,t}$ can be written as:

$$P^{HIRE}_{a,i,t} = \alpha^{HIRE}_a + \beta^{HIRE}_a . \ln(K^{INNOV})_i + X_{i,t-1}.\gamma^{HIRE} + Z^A_{i,t-1}.\delta^{HIRE} + \varepsilon^{HIRE}_{a,i,t}$$

and

$$P^{EXIT}_{a,i,t} = \alpha^{EXIT}_a + \beta^{EXIT}_a . \ln(K^{INNOV})_i + X_{i,t-1}.\gamma^{EXIT} + Z^A_{i,t-1}.\delta^{EXIT} + \varepsilon^{EXIT}_{a,i,t}$$

where $\ln(K^{INNOV})_i$ is our measure for innovative capital, $X_{i,t-1}$ is a set of labour demand factors (relative wages, tangible capital, value added, industry and size dummies) in firm i at time $t-1$, $Z^A_{i,t-1}$ is the vector of the employment shares of age groups, and the $\varepsilon^{HIRE}_{a,i,t}$ and $\varepsilon^{EXIT}_{a,i,t}$ are stochastic error terms. The main advantage of such a linear model is that it enables us to estimate the share of entries and exits for all age groups simultaneously, using joint generalised least squares, thus allowing to take into account potential correlations between entries and exits across age groups.

[3]See Aubert et al. (2004).

[4]Exits include workers who are fired, who retire, ends of short-term contracts and workers who leave the firm on a voluntary basis (either by resigning or on early retirement schemes). Unfortunately, our data do not allow us to distinguish between these various forms of exits.

Since we are interested in hiring opportunities and incidence of separations for older workers relative to younger ones, we decompose β_a^{HIRE} into two components: θ^{HIRE} that is common to all workers, and an age-specific component θ_a^{HIRE} (resp. θ^{EXIT} and θ_a^{EXIT} for β_a^{EXIT}). We constrain the θ_a^{HIRE} (resp. the θ_a^{EXIT}) to add up to zero to make the model identifiable:

$$\beta_a^{HIRE} = \theta^{HIRE} + \theta_a^{HIRE} \quad \text{and} \quad \beta_a^{EXIT} = \theta^{EXIT} + \theta_a^{EXIT}, \text{ for all } a$$

i.e.

$$\theta^{HIRE} = \frac{\sum \beta_{a'}^{HIRE}}{A} \quad \text{and} \quad \theta_a^{HIRE} = \beta_a^{HIRE} - \frac{\sum \beta_{a'}^{HIRE}}{A}$$

where A is the total number of age groups.

3 The data

The data we use come from several databases since we need to combine information on technology and workplace organisation, on the age and skill structure of the workforce, and on the level of capital and value-added. One rich source of information on new technologies and workplace organisation in France is the COI (*Changements Organisationnels et Informatisation*) survey. It was carried out at the end of 1997 and covers 4,283 firms with more than 20 employees in the manufacturing sector. Senior managers were asked questions about computer use and firm organisation as of 1997.

As the COI survey does not include data on the age structure of the workforce nor on wages, we draw on a second database, namely the DADS file (*Déclarations Annuelles de Données Sociales*) in order to examine wage bill shares for various age groups. This is an exhaustive dataset available on a yearly basis. It is built out of employers' mandatory reports and covers all employees of all firms in the French private sector. The DADS file provides information on the size of the firm and on the sector in which it operates. For each employee, it also provides information on hours and days worked during the past calendar year, gross earnings, age and occupation. The DADS also provides information on labour flows, by allowing to know whether employees have been entering or leaving the firm during the past calendar year[5]. Eventually, we find information on the financial structure of firms in a third database, namely the BRN (*Bénéfices Réels Normaux*). This database consists of firms' balance sheets and is collected by the tax administration. It includes some 600,000 firms in the private non financial non agricultural sectors each year and covers about 80% of total sales in the economy. This file provides us with a measure of value-added and physical capital[6].

Matching the DADS and BRN with COI and cleaning out firms with implausible changes in the total wage bill[7] reduces the sample to 3,817 observations in 1998. When analysing employment inflows and outflows, we use a larger dataset: we allow labour adjustments to take time, and thus pool our data over 1998-2000. We jointly estimate employment flows for all age groups in each firm. So, we restrict our sample to firms with at least one worker in each age group over the period. Eventually, we only keep firms with both inflows and outflows given that it makes little sense to study the relative employment flows into/out of the various age groups if there are no entry nor exit in a firm. This leaves us with 3,336 firms in 1998, 3,185 in 1999 and 3,053 in 2000.

Our dataset includes rich information on technology and workplace organisa-

[5] Entrants are defined as workers who are in an establishment of the firm at t and were not there at $t-1$ and, in a symmetric way, workers leaving the firm are those who were employed in an establishment of the firm at t and are not there at $t+1$. For the sake of consistency we eliminate firms for which the number of workers reported for t in $t+1$ differs from the number reported in t.

[6] Physical capital is defined as the stock of fixed assets registered at their historical costs.

[7] We eliminate firms for which the change of the total wage bill between year $t-1$ and year t is greater (or less) than its average value plus (or minus) five times its standard deviation. This reduces the sample by at most 2.5%.

tion, on the age and skill structure of the workforce, and on the level of capital and value-added. Regarding age, we consider 4 age groups:[20 to 29], [30 to 39], [40 to 49], and [50 to 59] years old. We do not consider workers aged 60 and above since, until 2003, legal retirement age in France was 60 so that firms' demand was not the main motivation for employment changes beyond that age.

Regarding innovation (our K^{INNOV} variable), we define 3 technological and organisational indicators. The COI database asks firms' senior managers about the proportion of workers using computers in several occupational groups. We use this information to construct a binary variable, $COMP$, equal to 1 if more than 40% of workers use computers in at least two occupations. $COMP$ is equal to 1 for 75% of the firms in the sample. Following Crépon et al. (2003), we define a second indicator of technological intensity: $INET$ is equal to one when the firm uses the internet either to have access to email or to advertise or collect information. This indicator is equal to 1 for 40% of the firms, and both $COMP$ and $INET$ are used simultaneously by 36% of the firms. In addition to technology, the COI survey provides very rich information on workplace organisation. Firms are asked whether they use quality norms, self-managed teams and quality circles, just-in-time production or delivery, multi-tasking, total quality management, whether delayering has taken place over the past 3 years... We build up a summary indicator of the use of innovative workplace practices, $ORGA$, defined as the sum of 13 different organisational devices. Thus doing, we consider that firms which have adopted a large number of these workplace practices are more innovative than firms which have adopted only a few of them. As compared to what is usually done in the literature, where organisational innovation is most often measured through binary variables (see Black and Lynch, 2001), the main advantage of our indicator is that it partially captures the intensity of organisational innovativeness.

13.3% of the firms in our sample use one innovative organisational practice and the proportion decreases as the number of devices goes up, down to 0.7% of firms using all 13 devices (See Table 1) .

Table 1 : Innovative Workplace Practices

Intensity	0	1	2	3	4	5	6
% of firms	14.20	13.31	11.58	10.85	10.56	8.57	6.65
Intensity	7	8	9	10	11	12	13
% of firms	6.73	5.03	4.40	3.72	2.52	1.18	0.70

Not suprinsingly, organisational innovativeness is lower in smaller firms (51% of the firms using 0 organisational devices have less than 50 employees) and higher in bigger ones (all 27 firms using 13 organisational devices have more than 200 employees)[8]. The correlations[9] between our three innovation indicators are always

[8]Complete tables of descriptive statistics are avalaible from the authors upon request.

[9]As $COMP$ and $INET$ are dichotomous variables, the correlation coefficients are Pearson point biserial correlations.

positive and significant, but perhaps lower than what could be expected, with the correlation coefficients ranging from 0.27 to 0.33.

The correlation between the use of new technologies or innovative workplace practices and the wage bill shares of workers within firms varies according to the age groups (see Table 2).

Table 2: Correlation coefficients between innovation indicators and wage bill shares by age group

	ORGA	*INET*	*COMP*
20 to 29 years old	-0.008	-0.032**	-0.001
30 to 39	-0.005	0.015	0.040**
40 to 49	0.044**	0.022	0.010
50 to 59	-0.029*	-0.009	-0.046**

Note : Estimates significant at the 5 (resp. 10) percent level are indicated by ** (resp. *).

The correlations between computer use or the intensity of organisational innovativeness are negative and significant, at least at the 10% level, for workers above 50 years old. Results are less sharp for other age groups. However, the share of workers aged 40-49 appears to be positively correlated with the use of new organisational devices and the same goes for computer use and the share of workers aged 30-39.

Correlations are much more significant when we focus on inflows and outflows, even if the values of the coefficients remain quite low.

Table 3: Correlation coefficients between innovation indicators and wage bill shares by age group

	ORGA	*INET*	*COMP*
Inflows			
20 to 29 years old	-0.017*	0.048**	-0.001
30 to 39	-0.092**	-0.015	-0.044**
40 to 49	-0.110**	-0.043**	-0.081**
50 to 59	-0.079**	-0.015	-0.046**
Outflows			
20 to 29	-0.115**	-0.038**	-0.057**
30 to 39	-0.122**	-0.045**	-0.063**
40 to 49	-0.126**	-0.054**	-0.072*
50 to 59	-0.063**	-0.021**	-0.033**

Note : Estimates significant at the 5 (resp. 10) percent level are indicated by ** (resp. *).

Apart from the correlation between internet use and the inflow of younger workers (aged 20-29) which is positive and significant, all other correlations are either negative or insignificant. Both inflows and outflows appear to be lower in firms using new technologies and innovative workplace practices, thus suggesting that innovation reduces labour turnover. Moreover, the relative impact of innovation variables on employment inflows and outflows varies according to the age groups.

The relationships between innovation variables on the one hand, and the wage bill shares and employment inflows/outflows by age group on the other hand have been computed so far without controlling for firms characteristics and without taking into account the fact that labour demand may be correlated across age groups within firms. The regression analysis that follows deals with both issues.

To complete our data description, a number of descriptive statistics relative to wage bill shares and inflows/outflows are provided in Table 4.

Table 4: Descriptive statistics

	20-29	30-39	40-49	50-59
Average wage bill share				
All occupations	0.15	0.31	0.33	0.21
	(0.09)	(0.11)	(0.10)	(0.11)
including:				
Managers	0.04	0.11	0.14	0.12
	(0.04)	*(0.09)*	*(0.09)*	*(0.09)*
Clerks	0.02	0.03	0.02	0.01
	(0.02)	*(0.03)*	*(0.03)*	*(0.02)*
Blue-collars	0.09	0.17	0.17	0.08
	(0.08)	*(0.10)*	*(0.09)*	*(0.06)*
Inflows (average share of entrants)				
	0.35	0.14	0.11	0.08
	(0.20)	(0.16)	(0.15)	(0.15)
Outflows (average share of workers leaving the firm)				
	0.28	0.15	0.12	0.15
	(0.21)	(0.17)	(0.17)	(0.19)

Notes: 1. For inflows and outflows, the average shares of workers entering or leaving the firm are computed using years 1998, 1999 and 2000.
2. Standard deviations are in parentheses

4 Results

4.1 Wage bill share estimates

4.1.1 Wage bill shares by age group

We first jointly estimate the wage bill shares for all age groups but the first one in 1998. Coefficients for workers aged 20-29 are estimated using the following homogeneity condition:

$$\gamma_j^{20-29} = -(\gamma_j^{30-39} + \gamma_j^{40-49} + \gamma_j^{50-59})$$

with $j \in J = \{K; VA; COMP, INET, ORGA\}$. Basic controls include 5 size and 6 industry dummies, along with the logs of value added, physical capital and relative wages.

Table 5 presents the results for wage bill shares estimated by JGLS in our basic specification. Firms that intensely use computers have a greater share of workers aged 30-39 in their wage bill and a lower share of workers aged 50 and above. The impact of the internet is very similar, both in terms of magnitude and significance, with innovative firms spending a greater share of their wage bill on workers in their thirties and a lower share on the oldest age group. Concerning the use of innovative workplace practices, they also tend to be positively correlated with the wage bill share of younger workers and negatively correlated with that of older workers. Workers aged below 40 are positively affected in firms using new organisational practices whereas the opposite holds for workers above 50.

The magnitude of these effects is not very large, though. When significant, absolute changes in the shares vary from 0.2 to 1.3 percentage point according to the age group. However, given the initial age structure of the workforce in our sample, such figures correspond to changes by 1 to 5.5% in the wage bill shares of the various groups for each type of technological and/or organisational innovation used by the firm. Overall, the effect of being employed in an innovative rather than non innovative firm is likely to be non negligible for workers aged 30-39 and 50-59, all the more that some 74% of the firms in our sample combine several types of innovation.

This anti-age bias of innovative firms is robust to a number of specification tests. Including 15 rather than 6 industry dummies for the manufacturing sector[10] does not change the general pattern of the results for computer use and innovative workplace practices. In both cases, workers below 40 account for a larger share of the wage bill in innovative firms and the opposite holds for workers aged 50 and above. However, the use of the internet stops being significant thus suggesting that this variable used to capture sectoral characteristics. Re-running regressions similar to that in Table 4 for employment rather than wage bill shares yields somewhat weaker results, but the general pattern of effects remains identical[11]. Older workers are negatively af-

[10] This corresponds to a 36 (rather than 16) post industry classification for the whole economy.

[11] A lower labour demand implies both lower employment and lower wages. Effects are thus stronger on wage bill shares than on employment shares, since the latter only captures part of the

Table 5

Wage bill shares by age groups - 1998

JGLS (coefficients x 100)

	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use (COMP)	0.421	1.268**	-0.464	-1.225**
	(0.380)	(0.447)	(0.440)	(0.466)
Internet (INET)	0.393	1.026**	-0.512	-0.908**
	(0.332)	(0.393)	(0.365)	(0.398)
Organisational innovations (ORGA)	0.169**	0.117*	-0.055	-0.230**
	(0.053)	(0.062)	(0.059)	(0.062)
Physical capital	-0.931**	-0.340	0.402*	0.869**
	(0.190)	(0.216)	(0.210)	(0.254)
Value Added	-0.196	0.063	-0.325	0.458
	(0.306)	(0.366)	(0.385)	(0.489)
Observations	3817			

Notes:

1. Coefficients in this table are estimates corresponding to $ORGA$, $COMP$ and $INET$, the log of physical capital, and of value added in the joint estimation of the wage bill share equations for all age groups but the first one in 1998.

Coefficients for workers aged 20 to 29 are estimated using the homogeneity conditions:

$\gamma_j^{20-29} = -(\gamma_j^{30-39} + \gamma_j^{40-49} + \gamma_j^{50-59}),\ j \in J = \{K; VA; COMP, INET, ORGA\}$

2. Basic controls include five size and six industry dummies as well as the log of relative wages (i.e. wages of all age groups relative to the 20-29 years old)

3. Estimated standard errors asymptotically robust to heteroskedasticity are reported in parentheses. Standard errors for the reference group (20-29 years old) are calculated using the Delta method. Estimates which are significant at the 5 (resp. 10) percent level are indicated by ** (resp. *).

fected in firms using innovative workplace practices, while workers aged 30-39 are positively affected in firms using computers and the internet. Another important issue has to do with the fact that innovative firms may reduce employment, with downsizing mainly affecting older workers for reasons independent from any skill obsolescence. This is the case if separation costs tend to be lower for older workers, for example due to the existence of early retirement schemes[12] or to the firing of older rather than younger workers being socially more "acceptable". Controlling for changes in firm employment over 1994-1997 leaves our results unchanged as compared to the basic specification, thus suggesting that the anti-age bias of innovation that we find is not entirely due to downsizing.

Eventually, results in Table 4 indicate that more capitalistic firms have a greater share of workers in their wage bill and a lower share of workers aged 20-29. This is consistent with what is found by Aubert and Crépon (2004) and is likely to be due to the fact that older workers are more numerous in older firms which are also more capitalistic. In contrast, the value added of the firm does not significantly impact the wage bill shares of any age group.

Overall, innovative firms appear to be biased against older workers. Workers aged 50 and above account for a lower share of the wage bill - and to a lower extent, of employment - in firms using new technologies and/or innovative workplace practices, whereas the opposite holds for workers below 40.

4.1.2 Wage bill shares by age and occupational groups

An interesting question regarding the age impact of innovation is whether it is uniform across occupations. Evidence in the literature shows that new technologies and organisational devices are biased in favour of workers in more highly skilled occupations. Are older workers more protected in such occupations or is the age bias independent from the skill dimension? In order to answer this question, we estimate wage bill shares by age and occupational groups (see Table 6). These regressions yield the average difference in the share of 3 occupations (managers and technicians, clerks, and blue-collars) between innovative and non innovative firms, as well as the differential effect of each type of innovation upon each age group within the 3 occupations.

Concerning computer use, the occupational effect appears to be consistent with results in the literature. Managers tend to be positively affected by innovation, whereas blue-collars are negatively affected. When controlling for the occupational structure, computer intensive firms still display a bias against older workers. Within the manager category, workers aged 30-39 are positively affected by computer use, whereas workers above 50 years old are negatively affected. One exception has to

demand effect. In table 4, we present results for wage bill share equations, which represent a broader approach for labour demand.

[12]The overall age structure of separation costs is a priori uncertain in France because firing costs tend to be lower for younger workers, but the existence of widespread early retirement schemes could make separation much cheaper for workers above 55.

Table 6
Wage bill shares by age and occupational groups - 1998
JGLS (coefficients x 100)

	Managers				
	Managers	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	1.518**	-0.534**	1.653**	0.394	-1.513**
	(0.177)	(0.175)	(0.276)	(0.285)	(0.317)
Internet	2.297**	-0.894**	1.602**	0.215	-0.923**
	(0.167)	(0.170)	(0.258)	(0.241)	(0.269)
Organisational innovations	0.036	0.076**	0.169**	-0.039	-0.206**
	(0.025)	(0.026)	(0.037)	(0.035)	(0.041)
Physical capital	0.133	-0.401**	-0.298*	0.273*	0.426**
	(0.108)	(0.107)	(0.139)	(0.151)	(0.170)
Value Added	1.549**	-1.043**	0.519**	0.500*	0.024
	(0.207)	(0.210)	(0.253)	(0.278)	(0.372)
	Clerks				
	Clerks	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	0.066	0.120	0.164	-0.098	-0.187*
	(0.077)	(0.091)	0.105	(0.103)	(0.097)
Internet	0.147**	0.128*	0.099	-0.019	-0.208**
	(0.059)	(0.067)	0.077	(0.076)	(0.067)
Organisational innovations	-0.042**	0.016	-0.002	-0.017	0.003
	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)
Physical capital	0.036	-0.084*	0.005	0.072	0.007
	(0.035)	(0.048)	(0.041)	(0.044)	(0.043)
Value Added	-0.025	-0.055	0.072	-0.095	0.078
	(0.061)	(0.091)	(0.073)	(0.076)	(0.076)
	Blue-Collars				
	Blue-collars	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	-1.583**	0.723**	-0.427	-0.739**	0.443
	(0.198)	(0.308)	(0.314)	(0.317)	(0.273)
Internet	-2.443**	1.123**	-0.597**	-0.992**	0.466**
	(0.179)	(0.247)	(0.254)	(0.245)	(0.212)
Organisational innovations	0.006	0.067	-0.045	0.042	-0.063*
	(0.027)	(0.041)	(0.041)	(0.042)	(0.035)
Physical capital	-0.169	-0.465**	-0.028	0.057	0.436**
	(0.113)	(0.141)	(0.129)	(0.136)	0.129
Value Added	-1.525**	0.847**	-0.429**	-0.922**	0.503**
	(0.208)	(0.189)	(0.181)	(0.202)	(0.185)
Observations	3,817				

Notes: 1. Coefficients for occupational categories are the averages over the four age groups, e.g. $\widehat{\widehat{\gamma}}^{clerk}_{ORGA} = \frac{1}{4}\sum(\widehat{\gamma}^{20-29,clerk}_{ORGA} + \widehat{\gamma}^{30-39,clerk}_{ORGA} + \widehat{\gamma}^{40-49,clerk}_{ORGA} + \widehat{\gamma}^{50-59,clerk}_{ORGA})$

Coefficients for age-by-occupation groups are the difference between the estimate and the coefficient for the corresponding occupation, e.g. $\widehat{\widehat{\gamma}}^{30-39,clerk}_{ORGA} = \widehat{\gamma}^{30-39,clerk}_{ORGA} - \widehat{\widehat{\gamma}}^{clerk}_{ORGA}$

Within an occupational category, coefficients for age groups therefore add up to zero.

2. Controls include the logarithm of the value-added and of the stock of capital along with five size and six industry dummies.

do with the youngest group (i.e. 20-29) which is negatively affected in firms using computers. This may be due to the fact that our manager category includes both managers and technicians and that proper managers are likely to be quite few in the youngest age group. So, the negative effect we capture here could be on technicians rather than on managers really. This does not mean that computer use has no effect on young managers. We indeed display a strong positive impact on the 30-39 year old group within the manager category, which may be driven by the impact of computer use on proper managers. If this is the case, it suggests that the age bias in favour of younger workers shows up slightly later in their career for workers in the most skilled group. In the clerk and blue-collar groups, the overall age effect displays a pattern very similar to that of managers: workers under 40 tend to be, if anything, positively affected by computer use, whereas the opposite holds for older workers.

As regards the internet, the results are very similar to those obtained for computer use. The average effect appears to be positive for managers and clerks, and negative for blue-collar workers. Within each occupational category, younger workers tend to be positively affected while older ones are negatively impacted. However, the age limit varies according to the occupational group: only the oldest group (i.e. 50-59) of managers and clerks is negatively affected, whereas the internet appears to become harmful to blue-collars as soon as they turn 30. One exception is again young managers who seem to be negatively affected by the web, as well as the oldest group of blue-collars who would be positively affected. For the latter, one possible explanation is that experience may partly substitute for the lack of educational skills.

Concerning new organisational practices, the effect on the occupational structure does not come up as significant except for clerks where it is negative. However, the age effect of innovation is confirmed within occupational groups with workers below 40 being positively impacted in the managerial group and workers aged 50 and above being negatively affected both in the manager and blue-collar groups.

From this second set of results, skills do not do not appear to protect older workers against the anti-age bias of innovation.

4.2 Employment inflows and outflows

Another interesting question regarding the anti-age bias of innovation is whether it is due to some form of skill obsolescence or whether it emerges for independent reasons. As already mentioned, one plausible explanation of the behaviour of innovative firms with respect to older workers relies on downsizing, if the burden of the adjustment is disproportionally borne by workers aged 50 and above. This is not very likely to be the case here, given that the correlations between our innovation variables and the wage bill shares of the various age groups remain unchanged after controlling for employment dynamics at the firm level. However, in order to get a more detailed view on this question, we jointly estimate the impact of *COMP*, *ORGA* and $INET$ on employment inflows and outflows for all age groups in each firm. If the share of exits is systematically higher for older workers in innovative firms, downsisizing and relative separation costs are likely to play a major role. In contrast, if part of the effect of innovation goes through hiring opportunities being different across age groups, this will indicate that downsizing is not the only driving factor behind the anti-age bias, and that some skill obsolescence may be at work.

As mentioned in Section 3, when estimating the share of entries and exits in each age group, we pool our data over 1998-2000. We do so in order to take into account the fact that employment adjustments may take time. One potential problem with this strategy is that, thus doing, we are likely to introduce some noise in our estimates, due to the fact that a number of firms which had not introduced any innovation by 1997 may have done so over 1998-2000. However, such a noise will make us consider as non innovative, firms with an age structure of employment flows very similar to that of our group of innovative firms. This will, if anything, bias our results towards zero.

Results are reported in Table 7. The average impact on employment flows varies according to the type of innovation. Computer use does not seem to affect neither entry nor exit. In contrast, firms using the internet seem to hire more workers, while new organisational practices would reduce both in and outflows with a stronger effect on the latter, though.

When coming to the age structure of employment flows, our results suggest that new technologies mainly affect hiring opportunities of the various age groups, whereas the impact of organisational innovations is essentially on exits. Computer use positively affects hirings of workers aged 30-39 and the same holds for the internet with workers aged 20-29. Both tend to lower inflows of workers between 40 and 49, and the internet also reduces hiring opportunities for the oldest group of workers (above 50). As regards outflows, computer use has no differential impact on the various age groups. The only significant effect comes from the internet which has a positive impact on exits for workers aged 30 to 39. Regarding new organisational devices, they have no differential impact on the various age groups as far as employment inflows are concerned. In contrast, they tend to reduce exit for workers aged 20-29, and to enhance it for workers above 50 and, to a lower extent, for those aged 30-39.

So, the use of new technologies tends to generate greater entry opportunities for younger workers and lower opportunities for older ones, while for organisational innovations, the age bias is mainly due to an increasing number of exits in the older group and to fewer ones for younger workers[13]. Such pattern of results indicates that the anti-age bias displayed by innovative firms is not entirely due to downsizing. When using new technologies, firms are more reluctant to hire older workers and

[13]One problem with our data is that we identify workers entering or leaving establishments, not firms. So, our measures of employment flows are overestimated, since workers moving from one establishement to another establishment in the same firm are considered as entering and leaving the firm at the same time. However, if we run regressions on the sub-panel of firms with only one establishment, our results are essentially unaffected. In particular, the effect of computer use and of the internet on the age pattern of hirings is reinforced when estimated on this sub-panel, where flows reflect true hirings or exits from firms. In constrast, the effect or organisational change on exits is not significant any more.

Table 7
Employment inflows and outflows by age group
JGLS (coefficients x 100)

	Inflows				
	Inflows	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	-0.404	0.427	0.506**	-0.760**	-0.173
	(0.369)	(0.390)	(0.235)	(0.233)	(0.269)
Internet	0.766**	0.898**	0.092	-0.588**	-0.401*
	(0.304)	(0.305)	(0.170)	(0.170)	(0.206)
Organisational innovations	-0.092*	0.025	-0.033	0.035	-0.027
	(0.048)	(0.048)	(0.027)	(0.027)	(0.032)
Physical capital	-0.995**	-0.062	0.013	-0.187*	0.236**
	(0.196)	(0.170)	(0.107)	(0.101)	(0.116)
Value Added	-2.013**	-0.284	0.007	-0.076	0.353*
	(0.365)	(0.304)	(0.179)	(0.184)	(0.199)
	Outflows				
	Outflows	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	-0.109	-0.084	0.235	-0.165	-0.015
	(0.435)	(0.371)	0.239	(0.239)	(0.304)
Internet	0.411	-0.258	0.411**	0.053	-0.206
	(0.339)	(0.278)	0.176	(0.172)	(0.233)
Organisational innovations	-0.140**	-0.165**	0.053*	0.037	0.074**
	(0.055)	(0.044)	(0.027)	(0.027)	(0.036)
Physical capital	-0.683**	-0.057	-0.211**	-0.228**	0.495**
	(0.229)	(0.162)	(0.103)	(0.103)	(0.135)
Value Added	-2.570**	-0.754**	0.064	0.277*	0.413*
	(0.401)	(0.275)	(0.170)	(0.161)	(0.222)
Observations	9,574				

Notes: 1. Dependent variables are the shares of entrants and of workers leaving the firm among the total number of workers in each age group.
2. Coefficients $\widehat{\theta}$ in this table are calculated from the estimates $\widehat{\beta}$ of $ORGA$, $COMP$ and $INET$ in the joint estimation of employment inflows and outflows for each age group.
Coefficients for employment flows are the averages over the four age groups, e.g.
$\widehat{\theta}^{HIRE}_{INNOV} = \frac{1}{4}\sum \widehat{\beta}^{a',HIRE}_{INNOV}$ for $a' \in \{1...4\}$, and $\widehat{\theta}^{EXIT}_{INNOV} = \frac{1}{A}\sum \widehat{\beta}^{a',EXIT}_{INNOV}$
Coefficients for age-by-type of employment flow are the difference between the estimates and the coefficient for the corresponding employment flow, e.g.
$\widehat{\theta}^{30-39,HIRE}_{INNOV} = \widehat{\beta}^{30-39,HIRE}_{INNOV} - \frac{1}{4}\sum \widehat{\beta}^{a',HIRE}_{INNOV}$ (where $INNOV$ = $ORGA$, $COMP$ or $INET$). Within each employment flow category, coefficients for age groups add up to zero.
3. Controls dated $(t-1)$ include the log of the value-added, of the stock of capital and of relative wages along with the employment shares of all age groups, and dummies for 5 size groups, 6 industries and 3 years.

tend to favour younger ones. This difference in hiring practices towards the various age groups can be due to older workers being endowed with less valuable skills. In this case, skill obsolescence would be one reason for the anti-age bias of innovation.

5 Conclusion

Wage bill share equations provide an insight of how new technologies and innovative workplace practices affect the optimal age structure of the labour force. From our study, we can draw several conclusions. First, innovative firms tend to be biased against age. They allocate, if anything, a lower share of their wage bill to workers aged 50 and above, while the opposite holds for workers below 40. Second, this anti-age bias of innovation shows up both in the whole population and within occupational categories. This suggests that skills do not completely protect workers against the labour market consequences of ageing. Third, firms' age structure is affected by innovation both through employment inflows and outflows. New technologies tend to reduce hiring opportunities for older workers and enhance them for younger ones, whereas organisational innovations mainly affect exits, which increase for older workers and decrease for younger ones. The difference we find in hiring practices between innovative and non innovative firms towards the various age groups suggests that skill obsolescence may be partly responsible for the declining employment prospects of older workers.

Of course, further work is needed in order to confirm this diagnosis. In particular, the issue of causality still has to be properly tackled. This requires to get panel information on innovation, which is still missing in most countries. The usual call for improved data is more than ever valid in the area of new technology and innovative organisational practices.

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