Training and Age-Biased Technical Change

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Abstract

Using a matched employer-employee dataset on the French manufacturing sector in the 1990s, we investigate how training incidence responds to technical and organizational changes across age groups.

Using a difference-in-difference approach across age groups and types of firms, we find that older workers in low-skill occupations lag behind in terms of training (in computer skills and in teamwork) when firms implement advanced information technologies. By contrast, there is no significant difference between age groups in the training response to advanced IT among workers in high-skill occupations, or in the training response to new organizational practices (among all skill groups).

These results suggest that a comparative disadvantage of older workers with regard to training in computer skills may be one cause of age-biased technical change. It severely affects low-skill older workers in firms implementing advanced information technologies.

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

JEL codes: J14; J24; J26; O30.

The prospect of a rapidly ageing workforce in OECD countries raises decisive issues. Will it reduce innovation and growth? How will retirement behavior evolve, and in particular, will older workers work longer? Answers to such questions depend on whether older workers will be able to adapt to an environment of rapid technical and organizational changes.

This paper takes a first step on this issue, by asking whether older workers receive more or less training when they are working in firms that undergo major technical and organizational changes. Specifically, we investigate training responses to technical and organizational changes in different age groups, using a matched employer-employee dataset relating to the French manufacturing sector in the 1990s. We use a difference-in-difference approach, comparing training incidence across age groups, in firms with more or less advanced technology and organizational practices. We separately consider training in the main task, training in computer skills and training in teamwork.

We find some evidence that older workers have a comparative disadvantage for training in contexts of technical change, but the evidence is limited to low-skill occupations, and we do not find that organizational change has similar effects. Specifically, using younger workers as a comparison group, we find that, in such low-skill occupations as clerks and blue-collar workers, those older than 50 suffer from reduced training incidence when firms implement advanced information technologies. Yet we also find that training responses are not systematically unfavorable to older workers: in particular, new organizational practices do not affect training incidence differently for older workers than for younger workers.

The main contribution of our paper is to put training at the forefront of the analysis of the literature on 'age-biased' technical change. Training can indeed be viewed as the missing link in the emerging literature suggesting that besides being skill biased, technical and organizational changes may be age biased against older workers. A first group of articles in that literature shows that older workers are slightly slower to adopt such innovating tools as computers. FRIEDBERG [2003] shows that successive cohorts of workers in the United States adopted computers at all ages, with a slight slowdown for workers close to retirement, which she interprets as the effect of a shorter payback period for computer training. WEINBERG [2004] shows that this slight slowdown covers sharp contrasts between high school graduates, whose computer use actually increases with experience, and college graduates, who adopt computers more towards the beginning of their careers. The picture is completed by KONING AND GELDERBLOM [2006]: using Dutch data, they show that not only does the share of workers using computers slowly fall with age, but the number and the complexity of tasks performed on computers also decrease. Overall, this first strand of literature finds some evidence that older workers have difficulties adopting computers, although the effect of age is perhaps weaker than expected. This may partly be due to a selection bias, if those older workers who were the least likely to adopt new tools have left the labor force.[1] A second strand of literature focuses on the effects of technical and organizational changes on the employment of older workers. BARTEL AND SICHERMAN [1993] find that persistently higher (industry-specific) rates of technical change induce older workers to retire later, whereas unexpected accelerations in the pace of change induce them to retire earlier. They interpret these results as evidence that training, as a long-run response to technical change, creates an incentive to retire later, whereas early retirement is the short-run response when workers have not received training in time. AUBERT, CAROLI AND ROGER [2006] estimate the impact of new technologies and new organizational practices on the labor demand for various age groups. *Ceteris paribus*, the wage bill share of older workers decreases in computerized firms with an innovative organization. Interestingly, in most of the above articles, the ability of older workers to take advantage of changes through training plays a key role in the interpretation of the results. In addition, views are contrasted: FRIEDBERG [2003] and AUBERT *et al.* [2006] tend to consider that older workers have a comparative disadvantage for training, whereas BARTEL AND SICHERMAN [1993] hold a more optimistic view. Overall, while these two strands of literature bring some support to the age-bias hypothesis, they also show the necessity to investigate training responses in more depth.

Our analysis thus deals with one of the key possible causes of age-biased technical changes: a supposed comparative disadvantage of older workers with regard to training in new technologies. It improves on previous descriptive work in BEHAGHEL [2006]. First, we use an original strategy to control for workers' selection: we construct proxies for individual workers' characteristics from a unique panel data set with worker data available since 1976, and use these proxies as controls for unobserved heterogeneity in the training equations. Second, we test the robustness of the results to alternative measures of technical and organizational changes used in the literature, although we would argue that our synthetic measures are more comprehensive. Last, we connect our results to the literature on the adoption of innovative tools, showing that the fact that older workers in lower occupations

[1] Selection is an important issue for older workers, as in many countries a significant share of older workers leaves the labor force before the legal (or usual) age of retirement. In France, for instance, 42% of men and 54% of women aged 55 to 59 were either unemployed or had left the labor force by 2002.

receive less computer training is not simply due to the fact that they are fewer to use computers, but also to the fact that there are fewer computer trainees among older workers using computers.

A clear limitation of our work – like most empirical papers in the literature on skill-biased and age-biased technical changes – is that, due to the lack of convincing instruments, a causal interpretation of the results rests on strong, untested assumptions. The key assumption needed in our case is the standard assumption of a difference in differences: comparing older vs. younger workers in firms with advanced vs. less advanced technology, we interpret the coefficient of the interaction of age and technology as evidence of age-biased technical change. This amounts to assuming that there is nothing else that can explain differences in age training profiles between firms with more or less advanced technologies. We acknowledge that alternative interpretations are plausible. For instance, it may be the case that unobservable characteristics of the management drive technology adoption and are correlated with prejudices against older workers. Though imperfect, we believe that our test brings interesting evidence on the role played by training in the age bias hypothesis. Presumably the most interesting finding lies in the contrasts between low-skill and high-skill occupations. It suggests that age and the shorter career horizon do not constitute a systematic barrier to training. Rather the difficulties faced by older low-skill workers are consistent with the view that they lack the basic computer literacy that is a prerequisite for training in advanced IT.

The article is organized as follows: Section 1 outlines the empirical strategy, Section 2 introduces the data, and results appear in Section 3, followed by concluding comments in Section 4.

1. Empirical approach

Our key empirical question is whether older workers suffer from a lower access to training in firms using advanced technologies and/or implementing innovative organizational practices. Formally, we would like to estimate the following model:

$$T_{ij} = \alpha_0 + \alpha_{old} Old_i + \alpha_c Comp_j + \beta_c Comp_j \times Old_i + \alpha_o Orga_j + \beta_o Orga_j \times Old_i + \mu_j + \nu_i + \varepsilon_{ij}, \quad (1)$$

where *i* is a subscript for the worker, and *j* denotes the different firms. T_{ij} is a measure of training investment; *Comp* and *Orga* measure the use of advanced IT and the implementation of new organizational practices (these two variables and the different training variables are presented in more details in the data section). *Old* is an indicator variable for older workers. ν_i and μ_j are unobserved worker and firm effects, possibly correlated with *Old*, *Comp* and *Orga*. The disturbance ε_{ij} is uncorrelated with the other independent variables.

The solutions we adopt to deal with the worker's and the firm's unobservable effects, ν_i and μ_j, are somewhat different. As mentioned in the introduction concerning the literature on the use of innovative tools, the worker's unobservable characteristics are likely to be correlated with his age, since only about half of older workers are still employed at age 50 to 59 in France. To deal with the omitted variable bias that this selection may induce, we rely on a proxy variable approach. As detailed in the data section below, we are able to build proxies for individual productive characteristics (namely, wage fixed effects at previous employers' and attachment to private sector employment). We use these proxies as controls in the training equations: if they are sufficiently correlated with the relevant unobservable individual characteristics, this should remove the omitted variable bias.

Abstracting from ν_i, let us now consider our approach to the firms' unobserved effect, μ_j. If we had a sufficient number of workers per firm, we would estimate the model within firms using fixed effects methods. A drawback of this, however, is that our data actually samples only one worker in every four firms (see data section below): one fourth of the observations would therefore be lost, and sample selectivity issues would arise. Our approach rather follows from a difference-in-difference strategy. To illustrate this in a simple way, let us assume that we have only two age categories and only two types of firms depending on the technology at use (the same reasoning would hold with organizational practices). *Old* is 1 for older workers, and *Comp* is 1 for firms with advanced IT (and 0 otherwise), and model (1) simplifies to:

$$T_{ij} = \alpha_0 + \alpha_{old} Old_i + \alpha Comp_j + \beta Comp_j \times Old_i + \mu_j + \varepsilon_{ij}. \qquad (2)$$

Grouping firm-worker matches in four categories according to age (younger / older) and to the technology at use in the firm (advanced / less advanced), consider the following difference-in-differences:

$$\begin{aligned}\Delta \quad \equiv \quad & E(T|Old=1, Comp=1) - E(T|Old=0, Comp=1) \\ & -(E(T|Old=1, Comp=0) - E(T|Old=0, Comp=0)) \\ = \quad & \beta + E(\mu|Old=1, Comp=1) - E(\mu|Old=0, Comp=1) \\ & -(E(\mu|Old=1, Comp=0) - E(\mu|Old=0, Comp=0))\end{aligned}$$

Therefore, the difference-in-differences identifies the parameter of interest, β, if and only if the following assumption holds:

$$\begin{aligned}& E(\mu|Old=1, Comp=1) - E(\mu|Old=0, Comp=1) \\ & \quad = E(\mu|Old=1, Comp=0) - E(\mu|Old=0, Comp=0)\end{aligned} \qquad (3)$$

This does not require that $E(\mu|Old=1) - E(\mu|Old=0) = 0$, a condition that would be violated if, for instance, firms that train their workers more tend to keep them longer, and therefore to have an older workforce. Assumption (3) allows for older workers to be overrepresented (or underrepresented) in firms that train their workers more; but it requires this to be the case in firms that use advanced technology in the same way as in firms that do not use advanced IT.

In practice, we do not compute β from the empirical analog to the above equation: we need to introduce covariates (in particular, proxies for the workers' individual effects), and the fact that the training variable is binary suggests using a latent variable model. We use a probit model:

$$T_{ij} = 1 \text{ if and only if } T^*_{ij} > 0 \text{ with} \qquad (4)$$

$$T^*_{ij} = \gamma_0 + \gamma_{old} Old_i + \gamma_c Comp_j + \beta_c Comp_j \times Old_i + \gamma_o Orga_j + \beta_o Orga_j \times Old_i + x_{ij}\theta + \eta_{ij}.$$

x_{ij} is a vector of controls that includes, in particular, the proxies for the worker's productive characteristics. The interpretation of the parameters of interest, β_c (respectively β_o) is subject to the usual caveat in difference-in-difference approaches. The interaction parameters identify age-biased technical change if and only if there is no other unobserved reasons by which high-tech firms / older worker matches differ from other matches. This condition may be violated if there are unobserved factors that simultaneously drive technology adoption and the choice of age training profiles in firms. For instance, it is well possible that some managers have a preference for advanced IT and negative prejudices against older workers. In the absence of experimental or quasi-experimental variations in the adoption of technology, we must be careful that the estimates do not necessarily have a causal interpretation.

It should be further noted that we do *not* need to identify coefficients α_c, α_o and α_{old} in equation (1). For these parameters, a difference-in-difference strategy is not possible, and estimates ignoring firm effects are likely to be biased. This is why we changed the notations to γ_c, γ_o and γ_{old} : these parameters encompass the causal effects α_c, α_o and α_{old}, and the impact of unobserved firm heterogeneity. We do not need to unbundle these effects to test for the role of training in the age-biased technical change hypothesis.

Finally, as detailed below, note that the model is estimated separately for different measures of training incidence, and for workers in higher and lower occupations.

2. The Data

We use two matched data sources. The data on the technology, the organizational practices, and the incidence of training comes from a French survey on organizational changes and computerization (*Changements Organisationnels et Informatisation*, COI) conducted at the end of 1997. The data used to control for selection comes from exhaustive social security records.

The COI survey is a matched employer-employee survey (see GREENAN AND MAIRESSE [1999] and the data appendix for a general presentation). We work with a random sample of about 2,500 manufacturing firms that completed a self-administered questionnaire on the use of information technologies and new managerial tools in 1994 and 1997. Small samples of employees (1 to 4) with at least one year of seniority have been randomly selected within each firm and interviewed, in the context of their homes, on workplace organization, technology use and training, which yields a sample of about 4,500 workers. The employee-level survey allows measuring the incidence of three types of training[2]: training in the main task, in computer skills, and in teamwork. Workers were asked the following questions: “in addition to your initial training, did your firm provide you with specific training in your current task?”, “did you receive specific training to teamwork?”, and “in addition to your initial training, did your firm provide you with specific training in your current task on computer?” From these three questions, we built three binary variables of training incidence. The questions were asked independently in different parts of the questionnaire and we use the three variables separately in the analyses. The questions about training in computers (respectively in teamwork) are asked only to workers who work on computers (respectively in teams). We assume that the other workers did not receive training in computer skills (respectively teamwork) and set the corresponding training variables to 0. We found this preferable to censoring the sample, as censoring would be endogenous, given that computer use may depend on the profitability of computer training. However, we will also consider a nested logit model for computers that distinguishes three groups of workers: those who do not use computers, those who use them without specific training, and those who use them and get specifically trained.

Note that the survey does not specify the period on which training incidence is reported. It may concern any training session provided by the employer. As such, training incidence rates are therefore not comparable across age groups if older workers have held their current job for longer. This leads us to control for seniority (tenure at the current employer) in our analyses of training incidence. Interestingly, adding tenure to the controls amplifies the drop in training incidence for workers above 50, but it has no effect on the comparison between firms with more or less advanced technology and/or organizational practices. It is therefore unlikely that this measurement problem biases the difference-in-difference analysis. Furthermore, we checked that training age profiles obtained with the COI dataset, once tenure is controlled for, are not too different to training age profiles obtained from another French data source over a similar period. The *Formation et Qualification Professionnelle* survey (FQP, 1993) consistently measures training incidence over a 5-year window. It does not, however, distinguishes between different types of training. But the bell shape of the training age profile found in the FQP data (BEHAGHEL [2006]) is broadly consistent with the bell shape for

[2] Note that the training sessions are provided and paid for by the firm. Post-schooling training paid by the worker is unusual in France.

reference firms in the COI data, once we control for tenure and for other composition effects (see section 3).

We build synthetic measures of computerization and organizational practices using a rich set of information from the firm-level questionnaire. Indeed, advanced technologies and managerial tools constitute clusters that cannot be captured directly through any single variable. However, it is possible to design a set of questions that seize different features of the technology and the organization. This information has to be synthesized to uncover the underlying latent variable. Following GREENAN AND MAIRESSE [2006], we rely on multiple correspondence analyses to synthesize information, building two measures of the use of new organizational practices and advanced technologies (the *Orga* and *Comp* variables). We standardize these variables to have mean 0 and variance 1. The *Orga* and *Comp* variables are reasonably correlated with simpler measures used in the literature (simple counts of organizational practices, for instance), but they arguably provide a better measure of technical and organizational changes. They can be described as follows: a firm with advanced IT (for which *Comp* takes high values) is equipped with a mainframe or a computer network, transfers data through an IT platform both internally and towards other entities (suppliers, clients, public agencies), uses the Internet and has an IT department[3]. A highly innovative organization (for which *Orga* takes high values) jointly uses various new organizational practices like quality certification, just-in-time, total productive maintenance, value analysis, outsourcing, independent profit centers and delegates indirect tasks like quality control or performance improvements to operators. *Comp* and *Orga* are both measured in 1997.

Finally, we use social security records of the employees' work history (the DADS administrative panel) to build proxies of the workers' productivity. The DADS data covers all private employment periods, starting in 1976. This unique data source has been used in several studies of wage careers (in particular, by ABOWD, KRAMARZ AND MARGOLIS [1999]). We use it to build two measures of individual productive characteristics. A first variable describes *attachment to private sector employment*. It is based on the total time spent outside of private employment between the first year the worker has been observed and the date of the survey (1997). As the source covers all private firms and as movements between the public and the private sectors are the exception (French civil servants benefit from lifetime employment by the government), these periods of absence are most likely non-employment

[3] The weights of the multiple correspondence analyses are given in the Data Appendix.

period (out of the labor force or unemployed). More precisely, we build our first proxy as the opposite of the ratio of the time spent away from private employment over the number of years since the worker entered employment (or since 1976 if the worker entered employment before 1976). Hence, high values in the indicator suggest a high attachment to employment. We interpret this as a proxy of high productivity for two reasons: first, the worker has accumulated more experience, and second, if firms fire the less productive workers in priority, having spent less time in unemployment signals higher ability. The second proxy is more standard, being a wage fixed effect from a Mincerian wage regression – call it the *individual wage fixed effect*. It is estimated in a covariance analysis of log wages controlling for education, gender, experience, industry, and time effects. The estimation is done for the period before the worker enters the firm that employs him or her in 1997 and that answers the firm-level COI survey. Indeed, we want to distinguish these individual characteristics of the worker from the characteristics of his or her current firm. The two proxies may depend on age by construction, and so we allow for interactions with age in the analyses.

Table A1 provides descriptive statistics. Panel A displays sample means for the whole sample and for two sub-samples of workers in more advanced firms (whose *Orga* and *Comp* values are above average). The most frequent type of training is training in the main task (about 50% of workers), slightly less frequent among older workers. More advanced firms train their workers more frequently; at this level of aggregation, the increase does not seem to vary across age groups. In addition, the incidence of training in computer skills and in teamwork increases with age and with the use of advanced IT and new organizational practices. The education data shows strong cohort effects, as younger generations are more educated. More educated workers also seem more frequent among firms with advanced IT and new organizational practices, whereas new technologies and new organizational practices are more frequent in large firms. Those large firms have larger populations of older workers. Finally, average tenure is somewhat higher in more advanced firms, which are also less frequently rural. Overall, these descriptive statistics show strong composition effects relating to firm size and to education levels. In the econometric analysis, we will control for these effects by introducing education and firm size indicators interacted with age.

The correlation coefficients in panel B show that there is no simple pattern connecting the age structure of the workforce to the use of new organizational practices and advanced technologies. By contrast, training correlates positively with the use or adoption of new organizational practices and advanced IT.

3. The Results

We start with two simple probit models of training incidence, generalizing the probit model of Section 1 to four age groups instead of two:

$$\Pr(T=1) = \Phi(c + \sum \alpha_a d_a + \delta\, Orga + \sum \beta_{orga,a} d_a \times Orga + \varsigma\, Comp + \sum \beta_{comp,a} d_a \times Comp) \qquad \text{(model 1)}$$

and

$$\Pr(T=1) = \Phi(c + \sum \alpha_a d_a + \delta\, Orga + \sum \beta_{orga,a} d_a \times Orga + \varsigma\, Comp + \sum \beta_{comp,a} d_a \times Comp + x\gamma)\,, \qquad \text{(model 2)}$$

where T is a binary variable indicating whether the worker has received training, *Orga* and *Comp* are measures of the firm's organization and technology; d_a is a dummy variable for age group a (30–39 year-old, 40–49 year-old and 50–59 year-old). Model 1 is estimated without controlling for composition effects. Model 2 controls for the worker's education (interacted with age group) and for his or her tenure in the firm (we distinguish four five-year tenure groups below twenty years of seniority, and one group for those with more than 20 years of tenure), for the size of the firm (interacted with the worker's age group), for the plant's localization (rural vs. urban) and for the frequency of early retirement in the industry. Controlling for early retirement is necessary as retiring early is a widespread practice in the French manufacturing sector and it may have an impact on training incidence by reducing the worker's career horizon.[4] The plant localization may also matter if urban firms find it easier than rural firms to hire the skills they need on the external labor market rather than to train their existing workforce. Table A1 contains descriptive statistics on all these control variables.

Models 1 and 2 are estimated separately for two occupational groups: managers and technicians/supervisors on the one hand, clerks and blue-collar workers on the other, and for three types of training: training in the main task, in computer skills, and in teamwork. Panel A of table 1 presents the results for clerks and blue-collar workers. We focus our comment on model 2. The top coefficients show the age training profile for a firm with average technology and organizational practices. Access to training in the main task (which is the most frequent

[4] See the Data Appendix for the construction of the industry-specific measures of early retirement frequency.

type of training) follows a bell curve, first increasing with age, then decreasing sharply (training incidence is 20.6 pp lower for workers above 50 than for workers aged 20 to 29). For training in computer skills or in teamwork, the profile is flatter before 50, but still decreases quite sharply after 50. Let us now consider the direct effect of technical and organizational changes, for the reference group of workers aged 20 to 29. If interpreted causally, the coefficients suggest that different types of changes (organizational vs. technical) call for different types of training (in the main task, in computer skills or in teamwork) following a pattern that seems intuitively appealing. Ceteris paribus, in firms where *Orga* is one standard deviation higher, training in the main task increases by 10.5 pp, while training in computer skills is unaffected. By contrast, in firms where *Comp* is one standard deviation higher, training in computer skills increases by 7.4 pp, while training in the main task is unaffected. Those estimates are statistically significant; they are also sizeable, equivalent to an increase by one fourth to one third of the average training rates. These effects are consistent with the few papers that have documented the complementarity between technological / organizational changes and skills showing that training increases with the adoption of new technologies and new workplace practices (BRESNAHAN *et al*. [2002], LYNCH AND BLACK [1998], ZAMORA [2006]). However, it should be kept in mind that they may partly overestimate this complementarity, as they may be spuriously driven by unobserved firm heterogeneity.

Our focus is on the interaction effects between the age group indicators and the *Orga* and *Comp* variables. Here again, results strongly differ by types of changes and types of training. There is no evidence of differences by age for training in the main task: none of the interaction coefficients is significant. By contrast, we find significant and sizeable differences for training in computer skills and, to a lesser extent, training in teamwork. Specifically, workers above 50 in firms with advanced IT suffer from a 14 pp reduction in training in computer skills compared to what is predicted by the main effects of age and IT. They witness a 9.8 pp increase in firms with innovative organizational practices.[5] We view the 14 pp reduction in training in computer skills as the key result of this paper. Interpreted causally, it suggests that older unskilled workers suffer from a comparative disadvantage to training in computer skills, so that firms using advanced IT prefer to focus their training investments on younger workers. By contrast, these workers receive additional computer training in firms

[5] One may fear that the opposite coefficients on *Orga* and *Comp* at age 50–59 are due to multicollinearity. This is however not the case. Although *Orga* and *Comp* are positively correlated (the correlation coefficient is .62), their effects can be separated. We checked that if we remove *Orga* from the estimation, the coefficients on *Comp* keep the same pattern. The interaction terms remain significant at the 1% level.

introducing new organizational practices. We are not sure how to interpret the latter result. One interpretation would be that the type of training needed to accompany organizational changes is more accessible to older workers – unfortunately, we do not have data on the content of the training in computer skills to test this hypothesis.

Turning to managers and technicians/supervisors (panel B), we find much less dramatic effects. Once controls are introduced, there is no significant difference in responses by age (the interaction effects are never statistically significant). This suggests that age is less decisive for driving training responses. One possible but partial explanation for that may lay in the quite high training rates among these workers (training in the main task concerns more than 80% of workers in these high-skill occupations). A more tentative explanation may be that these workers, due to their initial skills, learn more quickly so that training investments are profitable even for shorter career horizons.

To summarize, we find that older workers in lower occupations (namely, clerks and blue-collar workers) have reduced access to certain types of training in firms that use new technologies. But the results also show that such a bias against older workers' training is far from systematic: we don't find the same evidence for older managers and technicians/supervisors, and there is no evidence that new organizational practices are unfavorable to training older workers in any occupational groups.

Limitations of the analysis so far have to do with selection, measurement, and the distinction between impacts on computer use and on computer training. First, as shown by AUBERT *et al.* [2006], technical and organizational changes have adverse employment effects on older workers: more advanced firms recruit fewer of them and dismiss them more frequently. This gives rise to a selection problem: if older workers in more advanced firms are selected along unobserved characteristics that impact training, the estimates of the training equations are biased. Second, measuring the cluster of practices and tools that define advanced firms involves choices, which makes it useful to check the robustness of the results to alternative measures. Last, we have so far grouped workers who do not use computers with workers who use computers without specific training, such that a refinement involves separating the two. The rest of this section addresses these three issues in turn.

Workers' selection

Using the employer section of the COI survey matched with administrative firm data on employment and worker flows, AUBERT *et al.* [2006] show that technological and organizational changes reduce the employment of older workers. However, we cannot use the same (firm-level) data in order to control for selection in our (individual-level) training equations. To deal with the omitted variable bias that the selection may induce, we therefore use an alternative approach relying on proxy variables. We use the two proxies presented in Section 2 as controls in the training equations.

Before presenting the augmented selection equations, it is useful to check whether our proxies indeed seem to be related to the selection of older workers in more advanced firms. We estimate the following "selection equation":

$$proxy = c + \sum \alpha_a d_a + \beta\, Orga + \sum \beta_a d_a \times Orga + \gamma\, Comp + \sum \gamma_a d_a \times Comp + x\delta + \varepsilon, \quad \text{(selection model)}$$

where *proxy* is one of the two proxies (either the *attachment to private sector employment*, or the *individual wage fixed effet*), *Orga* and *Comp* are measures of the firm's organization and technology; d_a is a dummy variable for age group *a* (30–39 year-old, 40–49 year-old and 50–59 year-old), *x* is a vector of controls, and ε is the error term. If older workers in more advanced firms are specifically selected, we expect interaction coefficients β_{50-59} and γ_{50-59} to be positive. Table 2 presents the results estimated separately for each proxy and for each occupational group. As shown in panel A, older clerks and blue-collar workers employed in firms that use more advanced technologies have more favorable characteristics than younger ones. Concerning attachment to employment, the interaction coefficients are positive and significant for workers above age 40. Concerning the wage fixed effect, they are significant only for workers aged 40–49, but the lack of significance at age 50–59 may be due to the smaller sample size (indeed, the point estimate at age 50–59 is very close to the coefficient at age 40–49). The effects are sizeable: older clerks and blue-collar workers employed in firms where *Comp* is one standard deviation higher used to earn 20% higher wages at their previous employers'. By contrast, there is no evidence of specific selection of older workers among clerks and blue-collar workers in firms that use new organizational practices more intensely, and no more evidence of selection among managers and technicians/supervisors in firms with more advanced technology and organizational practices. To summarize, the results of the selection equation are somewhat mixed. Concerning managers and technicians/supervisors, the proxies do not seem to capture a different treatment of older workers in more advanced firms, but they do for clerks and blue-collar workers in firms that use more advanced technologies. They can therefore be used to control for selection bias in these occupations, which serves our purposes since it is for clerks and blue-collar workers that the training equations yield the stronger results.

Table 3 presents the results obtained when adding the selection proxies, interacted with age, to the training equations (model 3).[6] The bottom part of the table displays the p-value of the test that the selection proxies have no impact on training incidence. One cannot reject the null hypothesis at usual significance levels. Hence, even though the proxies are connected to the selection of older clerks and blue-collar workers, they do not have any significant effect on training incidence. As a consequence, the coefficients on *Orga* and *Comp* are very close to those of model 2 in table 1. The key findings remain valid: older clerks and blue-collar workers are less frequently trained in computer skills and in teamwork when firms adopt advanced IT, but there is little evidence of a disadvantage of older managers and technicians/supervisors with regard to training. Concerning training in teamwork, the negative effect of computerization for older clerks and blue-collars remains only marginally significant.

[6] As shown by the number of observations in table 2, the proxies are not available for all workers. To avoid restricting the sample, we impute the median value of the category when the proxy is missing. In these cases, we add a dummy variable indicating that the proxy was missing, interacted with age group, in the training equation.

Alternative measures of new organizational practices and technology

The synthetic *Orga* and *Comp* variables we have used so far attempt to capture clusters of practices and technologies. Nevertheless, the literature has sometimes relied on simpler measures that perhaps have the advantage of being more transparent, even though they do not account for the complementarities between practices and tools. It is important to check whether our results are robust to changes in the measure used, to which end we replicate our analysis with the same indicators as AUBERT *et al.* [2006]. The new *Comp* variable is a binary variable that is equal to 1 if more than 40% of workers use computers in at least two occupations, and the new *Orga* variable is the sum of 13 organizational devices. The old and new *Orga* variables tend to be highly correlated (the correlation coefficient is .89), while the two *Comp* variables are more different (correlation coefficient: .31).

Table 4 presents the replication of the results of table 3 with these new measures. New organizational practices still have a positive impact on training in the main task for all age groups. The key result of table 1 and 3 is confirmed: older clerks and blue-collar workers is less frequently trained in computer skills when firms adopt advanced IT. However, the coefficient on the interaction is somewhat smaller (-9.6 pp) and only marginally significant; moreover, other effects are no longer significant. Concerning training in teamwork, we do not find any significant effect of computerization for older clerks and blue-collars (the point estimate becomes positive). This difference probably stems from the fact that the two *Comp* variables do not measure the same thing: the new *Comp* variable measures the diffusion of computer use within the firm, whereas the old one measures the complexity of the IT used. We believe that a measure of the complexity of IT is more relevant. Overall, however, our main result is robust to the choice of the IT measure.

Computer use and computer training

We have considered so far that workers who do not use computers do not receive training in computer skills, and we have grouped them with workers who declare that they use computers without receiving specific training. In order to interpret our results further, it is useful to separate computer use and computer training. We consider a multinomial model with three possible outcomes: the worker does not use a computer; uses computers without receiving specific training; or uses computers and receives computer training. These outcomes can be viewed as the result of an optimization process in which the decisions of computer use and computer training are taken jointly. Unobserved characteristics that affect the last two outcomes (computer use with and without training) are likely correlate. We therefore estimate a nested logit model with two branches (use / not use) and two alternatives within the first branch (train / not train). The results are displayed in table 5, where we report the predicted impact of higher values in *Orga* and *Comp* on the probability of each outcome. Among clerks and blue-collar workers (panel A), the probability of not using computers decreases significantly in firms with advanced computerization, except when the worker is above 50. Symmetrically, the probabilities of using computers with and without training tend to increase below 50, while the increase is smaller and hardly significant concerning computer use *without* training. And, concerning computer use *with* training, we again find a sharp contrast between workers above and below 50: the probability increases significantly for younger ones, but it tends to decrease for older workers. It thus appears that there is a specific disadvantage of older clerks and blue-collar workers with regard to computer training (rather than to computer use solely). A tentative interpretation is that older workers' disadvantage is related to advanced uses of computers that require specific training rather than to simple uses that do not involve specific training. This interpretation is consistent with the fact that our *Comp* variable measures the implementation of advanced IT in the firm. The last two columns of panel A display naive probit estimations for comparison purposes, and the second probit model confirms that, among computer users, the implementation of advanced IT in the firm significantly reduces the probability that older workers receive computer training.

Concerning managers and technicians/supervisors, older workers do not distinguish themselves from younger ones. The probability of not using computers declines similarly for workers aged 40–49 and 50–59 in firms with advanced computerization. Moreover, the probability of using computers and receiving training increases similarly in those two groups (although not significantly at conventional levels).

Overall, this decomposition confirms the specificity of older clerks and blue-collar workers with regard to computer training. The difference is not simply due to the fact that they do not need computers in their tasks, as the probability of receiving training in computer skills tends to decline after 50, even among computer users.

4. Discussion

Our main finding is that older clerks and blue collars receive significantly less training in firms that have adopted advanced IT, compared to what the main effects of age and IT would separately predict. But we do not find any negative age effect in the case of training to the main task, while results on training in teamwork are not fully robust. Moreover, we do not find any disadvantage for older workers when firms implement new organizational practices.

These findings give empirical support to the hypothesis of age-biased technical change caused by a comparative disadvantage of *some* older workers to *some* forms of training. The fact that the age bias does not appear for high-skill workers nor when firms implement organizational change is interesting. It suggests that the bias is due to accelerated skill obsolescence for the particular group of low-skill older workers. Indeed, if it was due to a systematic inability of older workers to work and learn skills in a changing environment, it should also be evident in firms with innovative organizational practices (that include multitasking, job rotation, etc.). If it was due to the shortness of the older workers' horizon to get the return from training investments, training incidence would not rise in response to organizational change. Our results rather suggest that the age bias is caused by a problem that specifically impacts older low-skill workers in the context of technological change. Accelerated skill obsolescence and difficulties to learn computer skills is a plausible explanation. Older workers in the nineties were educated in a world without computers, and may thus lack the computer literacy required for work on complex IT systems and for further computer training. If they are in low-skill occupations, they also likely lack the general skills that could help to overcome this difficulty.

There is another possible interpretation why the training responses to technical change among older workers (in lower occupations) are different than the response to organizational change. It could be that organizational changes require a firm-wide program (and therefore firm-wide training) whereas IT training can be highly individual. This would explain why we observe significant age effects in computer training and not in training to the main task.[7] To further

[7] We also find negative age effects for training in teamwork among clerks and blue-collars (though the effect is less robust than for computer training: see tables 3 and 4). Despite the fact that teamwork has a collective dimension, this is not inconsistent with a distinction between individual and firm-wide training. Firms can be selective in their choice of whom is leading the teamwork and therefore gets the training (in our sample, less than 20% of workers have received training in teamwork).

investigate this possibility, we would need data with larger samples of workers in each firm. Note that it were true, it would reinforce our findings in favor of the age-bias hypothesis.

Comparing our results with previous ones in the literature, we can first confirm that a sizeable share of older workers receives computer training. This is consistent with the slow and non-systematic decrease in computer use with age found in the literature (WEINBERG [2004], FRIEDBERG [2003], BORGHANS AND TER WEEL [2002]). But our key finding is that this share does not increase among older clerks and blue-collar workers when firms introduce advanced information technologies, which may be a sign that these more complex technologies are out of reach for older low-skill workers. Such an interpretation is consistent with findings by KONING AND GELDERBLOM [2006] according to which complex tasks performed on computers are less frequent among older workers. The advantage of using matched employer-employee data is that we can observe how, in the 1990s in France, firms implementing advanced information technologies tended to specialize younger workers (under 50) in these new technologies at the expense of workers over 50.

A remaining question is: will the disadvantage of older low-skill workers in learning computer skills last over the next decades? The fact that workers aged 40-49 received additional training in firms using advanced IT suggests that things may evolve favorably: older workers from the next generations probably have better computer literacy, making training easier. Besides generation effects, perhaps a key variable is self-confidence. Studies in psychology suggest that older workers' underconfidence may be part of the explanation, as experiments show that, compared to what they actually know, older workers underestimate their knowledge in the domain of computers while they do not underestimate their general knowledge (MARQUIÉ *et al.* [2002]): if this misrepresentation is a major cause of the insufficient training response, it should progressively disappear as more and more older workers succeed in learning computer skills. These are of course only conjectures: panel data with repeated information on training and technical change should help to address this issue empirically and to complete the econometric analysis of the endogeneity of technical and organizational changes.

ACKNOWLEDGMENT

We thank the editor and two referees for numerous helpful suggestions. We also thank David Blau and seminar participants at Crest and University of North Carolina. All remaining errors are ours.

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Data Appendix

The main data source is the COI survey (*Changement organizationnel et informatisation*, 1997), a French matched employer-employee survey designed to produce accurate information on computerization and organizational change at the firm and at the job level (see www.enquetecoi.net). A random sample of 3019 firms with more than fifty employees in manufacturing and food industries have been interviewed through a business survey with a self-administered questionnaire of four pages. The Ministry of Industry (SESSI) conducted the employer section of the survey in manufacturing while the Ministry of agriculture (SCEES) took care of food industries.

The questions that we use to measure computerization and organizational change are displayed in tables A3 and A4. Question numbers are those of the questionnaire (our presentation does not follow the order of the questionnaire). Descriptive statistics on the computerization and organizational indexes built from these questions appear in table A1. The list of selected firms has then been matched with an administrative data file designed to control social contributions (DADS – "*Déclarations Annuelles de Données Sociales*" data file). Each person employed by the firm during a year is registered in this file along with the number of days worked and earnings. This file enabled us to take small, random samples of two or three employees with at least one year of seniority within each firm, leading to a sample of 6,796 employees. While selecting workers, we have kept information about their past trajectory registered in the DADS panel. This historical file is used in this article to compute the proxies for individual productivity.

The Ministry of Labor (DARES) conducted the Labor force section of the survey. Employees were interviewed by phone, in the context of their homes, or face to face when they could not be reached by phone. The *Centre d'Etudes de l'Emploi* (under the direction of Nathalie Greenan) conducted the design of the survey device (method and questionnaires) and coordinated the survey implementation. The survey benefited from high response rates both on the firms' side (82%) and on the employees' side (71%). High response rates, along with the randomness of the samples and the independent implementation of the two surveys guarantee the quality of the information.

Measures of new organizational practices and of computerization

The firm-level questionnaire asks a set of questions that focus on different features of the use of IT and new organizational practices. This information has to be synthesized to uncover the underlying technological or organizational latent variable. We rely on multiple correspondence analyses to synthesize information, using the measures built in GREENAN AND MAIRESSE [2006].

Comp is measured through an analysis involving 15 discrete variables with 2 to 5 items. Some items are presented in table A5, together with their distribution in terms of the percentage of firms for 1994 and 1997. Some questions are formulated symmetrically for 1994 and 1997 but others are not. As far as computer use is concerned, this is true for outsourcing IT and telephony and network functions and for the Internet (see table A1, questions 3.9, 3.10, 20.1, 20.2, 20.3). For outsourcing, the questions are formulated in the following fashion: "Does your company outsource any of the following tasks in 1997?" (yes/no) and "What is the change in the % of employee affected since 1994?" (+,=,-). The first factor of the multiple correspondence analysis can be interpreted clearly as measuring the complexity of IT use. It separates firms with an advanced computerization (complex equipment infrastructure, intense computerized data transfers, internet use, IT and a phone and network departments) from firms with no or very basic equipment, no computerized data transfers, and no IT department. Our computerization index in 1997 is given by the firms' coordinate on this first factor.

Symmetrically, the use of new organizational practices is measured through an analysis using 15 variables with 2 to 4 items in 1997. Table A6 gives their distribution and indicates variables that have been estimated in 1994. As for computer use, new organizational practices cluster on the first factor of the correspondence analysis: firms using just-in time practices, total productive maintenance, and value analysis, and with a complex structure, are opposed to firms with a simple structure having no just in time practices and no quality certification. The organization index in 1997 is built as in the computer use case, from the coordinates of firms and weights of items on this first factor (see last column of table A6).

Training Incidence

The questions used to measure access to training are the following:

Q25. In addition to your initial training, did your firm provide you with specific training in your current task? (Yes/No)

Q40: Do you sometimes do your work in teams or collectively?
Q40bis d. Did you receive specific training to teamwork? (Yes/No)

Q52: Do you use, even occasionally:

- a personal computer
- a mainframe computer
- other information technology?

Q60. Since which year have you been working on computer?
Q61. In addition to your initial training, did your firm provide you with specific training in your current task on computer? (Yes/No)

This calls for two remarks. First, most questions only measure access to training through training incidence. However, a rough measure of training intensity (more or less than three days) is available for computer training. We checked that training profiles are qualitatively not modified when we count as training only the sessions that last more than three days.

Second, the questions do not specify the period in which the training session has occurred. Presumably, the period considered is longer for older workers. This requires that we control for seniority (tenure at the current employer) in the training equations.

Frequency of early retirement

Early-retirement frequency is measured by the evolution between 1995 and 2000 of the size of the cohort aged 55–59 in 2000 in employment. This measure is based on a comprehensive administrative dataset on total employment in 36 industries in France. The data has been used by AUBERT [2004] who kindly provided it to us.

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TABLE 1: TRAINING PROFILES ACCORDING TO NEW ORGANIZATIONAL PRACTICES AND TECHNOLOGY

Panel A: Clerks and blue-collar workers

	Dependant variable: incidence of training...					
	... in the main task		... in computer skills		... in teamwork	
	(1)	(2)	(1)	(2)	(1)	(2)
Age effects (ref. *20-29 year old)*						
30-39 year old	-0.013	0.210	0.020	-0.088	0.001	-0.019
	[0.028]	[0.198]	[0.022]	[0.130]	[0.012]	[0.075]
40-49 year old	-0.044	0.383*	0.004	0.004	0.008	-0.014
	[0.029]	[0.200]	[0.022]	[0.160]	[0.013]	[0.076]
50-59 year old	-0.136***	-0.200	-0.036	-0.206***	0.009	-0.223***
	[0.032]	[0.269]	[0.025]	[0.059]	[0.017]	[0.013]
New organizational practices						
Orga	0.113***	0.105***	-0.013	-0.019	0.015	0.010
	[0.029]	[0.030]	[0.021]	[0.022]	[0.014]	[0.013]
Interaction effects (reference: *20-29 year old*)						
Orga x [30-39 year old]	-0.034	-0.041	0.029	0.018	-0.001	0.001
	[0.035]	[0.037]	[0.026]	[0.026]	[0.017]	[0.016]
Orga x [40-49 year old]	-0.032	-0.044	0.012	0.012	-0.009	-0.006
	[0.036]	[0.038]	[0.027]	[0.028]	[0.016]	[0.015]
Orga x [50-59 year old]	-0.053	-0.046	0.106***	0.098***	0.018	0.022
	[0.045]	[0.048]	[0.035]	[0.035]	[0.020]	[0.018]
Computerization x age effects						
Comp	0.022	-0.017	0.082***	0.074***	0.015	0.005
	[0.030]	[0.034]	[0.023]	[0.024]	[0.014]	[0.014]
Interaction effects (reference: *20-29 year old*)						
Comp x [30-39 year old]	0.018	0.034	-0.030	-0.038	-0.008	-0.005
	[0.035]	[0.040]	[0.028]	[0.029]	[0.017]	[0.017]
Comp x [40-49 year old]	0.011	0.017	-0.008	-0.019	-0.003	0.002
	[0.036]	[0.042]	[0.028]	[0.029]	[0.016]	[0.017]
Comp x [50-59 year old]	0.036	0.042	-0.072**	-0.140***	-0.032	-0.043**
	[0.044]	[0.051]	[0.034]	[0.038]	[0.020]	[0.021]
Controls for composition effects	No	Yes	No	Yes	No	Yes
Number of observations	2716	2716	2704	2704	2710	2710
Log likelihood	-1784	-1731	-1228	-1110	-548	-529

…/…

TABLE 1 (continued)

Panel B: Managers and technicians/supervisors

	Dependant variable: incidence of training...					
	... in the main task		... in computer skills		... in teamwork	
	(1)	(2)	(1)	(2)	(1)	(2)
Age effects (ref. *20-29 year old)*						
30-39 year old	0.060*	0.346*	0.072*	-0.108	0.078*	0.123
	[0.034]	[0.210]	[0.042]	[0.377]	[0.040]	[0.344]
40-49 year old	0.043	0.069	0.082**	-0.343	0.136***	0.587*
	[0.034]	[0.305]	[0.041]	[0.334]	[0.040]	[0.314]
50-59 year old	-0.030	-0.173	-0.012	-0.655***	0.146***	0.308
	[0.040]	[0.386]	[0.045]	[0.124]	[0.048]	[0.417]
New organizational practices						
Orga	0.072*	0.073*	0.028	0.006	0.078**	0.065*
	[0.039]	[0.043]	[0.042]	[0.046]	[0.038]	[0.039]
Interaction effects (reference: *20-29 year old*)						
Orga x [30-39 year old]	-0.015	-0.034	-0.019	-0.011	-0.052	-0.037
	[0.046]	[0.050]	[0.049]	[0.053]	[0.043]	[0.045]
Orga x [40-49 year old]	-0.023	-0.045	0.010	0.026	0.007	0.015
	[0.046]	[0.050]	[0.049]	[0.053]	[0.044]	[0.046]
Orga x [50-59 year old]	-0.006	-0.035	-0.003	-0.018	-0.050	-0.054
	[0.050]	[0.055]	[0.057]	[0.062]	[0.048]	[0.050]
Computerization x age effects						
Comp	0.054	0.044	0.039	0.031	0.002	-0.013
	[0.037]	[0.040]	[0.045]	[0.048]	[0.040]	[0.042]
Interaction effects (reference: *20-29 year old*)						
Comp x [30-39 year old]	-0.011	-0.013	0.049	0.045	0.029	0.035
	[0.044]	[0.047]	[0.052]	[0.056]	[0.046]	[0.047]
Comp x [40-49 year old]	0.018	0.004	0.041	0.028	0.020	0.026
	[0.045]	[0.049]	[0.052]	[0.057]	[0.045]	[0.048]
Comp x [50-59 year old]	0.032	-0.015	0.102*	0.031	0.075	0.047
	[0.051]	[0.059]	[0.058]	[0.065]	[0.050]	[0.054]
Controls for composition effects	No	Yes	No	Yes	No	Yes
Number of observations	1667	1667	1659	1659	1661	1654
Log likelihood	-940	-907	-1109	-1068	-854	-819

Source: COI survey, employer section (SESSI, SCEES) and employee section (DARES), 1997.
Note: Probit models (marginal effects evaluated at sample mean). Standard errors are computed using the delta method. They are robust to cluster effects between workers of the same firm. Marginal effects are very similar when computed as the average of individual marginal effects over the sample. Controls for composition effects in model (2): tenure, education interacted with age group, firm size interacted with age group, frequency of early retirement in the industry, and plant's localization (rural dummy).

TABLE 2: SELECTION INDICATORS ACCORDING TO NEW ORGANIZATIONAL PRACTICES AND TECHNOLOGY

	Panel A: Clerks and blue-collars				Panel B: Managers and technicians/supervisors			
	Individual wage fixed effect		Attachment to private sector employment		Individual wage fixed effect		Attachment to private sector employment	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Age effects (ref. *20-29 year old)*								
30-39 year old	-0.034	0.099	10.598	2.584	0.123	0.198	14.406	8.645
	[0.065]	[0.191]	[1.154]***	[2.984]	[0.080]	[0.124]	[1.816]***	[3.030]***
40-49 year old	-0.035	-0.042	16.993	4.215	0.115	0.186	26.179	16.748
	[0.066]	[0.210]	[1.143]***	[3.547]	[0.077]	[0.133]	[1.749]***	[3.018]***
50-59 year old	-0.207	-0.459	19.618	10.288	0.253	0.160	29.431	21.753
	[0.082]**	[0.307]	[1.172]***	[4.369]**	[0.089]***	[0.189]	[1.787]***	[3.106]***
New organizational practices								
Orga	0.056	0.047	2.834	2.001	0.124	0.146	1.691	1.753
	[0.074]	[0.076]	[1.294]**	[1.130]*	[0.075]*	[0.083]*	[2.182]	[1.786]
Interaction effects (reference: *20-29 year old*)								
Orga x [30-39 year old]	0.046	0.059	-3.235	-2.047	-0.059	-0.070	-2.135	-2.102
	[0.085]	[0.087]	[1.479]**	[1.300]	[0.092]	[0.100]	[2.384]	[2.013]
Orga x [40-49 year old]	-0.085	-0.073	-3.153	-2.491	-0.040	-0.056	0.154	-0.552
	[0.082]	[0.087]	[1.465]**	[1.271]*	[0.092]	[0.098]	[2.257]	[1.888]
Orga x [50-59 year old]	-0.087	-0.067	-3.080	-2.432	-0.032	-0.053	-1.286	-1.843
	[0.114]	[0.110]	[1.514]**	[1.354]*	[0.115]	[0.122]	[2.346]	[1.972]
Computerization x age effects								
Comp	-0.052	-0.121	-4.009	-2.140	0.104	0.136	-0.834	0.192
	[0.070]	[0.079]	[1.369]***	[1.225]*	[0.075]	[0.083]	[2.101]	[1.984]
Interaction effects (reference: *20-29 year old*)								
Comp x [30-39 year old]	0.029	0.092	4.090	1.497	-0.065	-0.104	0.476	0.341
	[0.080]	[0.090]	[1.523]***	[1.385]	[0.092]	[0.099]	[2.298]	[2.189]
Comp x [40-49 year old]	0.126	0.196	5.536	3.116	-0.116	-0.127	-0.042	-0.887
	[0.081]	[0.089]**	[1.514]***	[1.382]**	[0.091]	[0.100]	[2.191]	[2.070]
Comp x [50-59 year old]	0.161	0.212	5.732	2.852	-0.090	-0.082	1.914	0.687
	[0.114]	[0.133]	[1.546]***	[1.401]**	[0.119]	[0.123]	[2.235]	[2.143]
Controls for composition effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	2003	2003	2501	2501	1316	1316	1531	1531
R-squared	0.01	0.03	0.16	0.36	0.02	0.04	0.30	0.44

Source: COI survey, employer section (SESSI, SCEES) and employee section (DARES), 1997; DADS panel, 1976–96.
Note: OLS models. Controls in model (2): tenure, education interacted with age group, firm size interacted with age group, frequency of early retirement in the industry, and plant's localization (rural dummy).

TABLE 3: TRAINING PROFILES – CONTROL FOR SELECTION

	Panel A: Clerks and blue-collar workers			Panel B: Managers and technicians/supervisors		
	Dependant variable: incidence of training...			Dependant variable: incidence of training...		
	... in the main task	... in computer skills	in teamwork	... in the main task	... in computer skills	in teamwork
	(3)	(3)	(3)	(3)	(3)	(3)
Age effects (ref. *20-29 year old)*						
30-39 year old	0.244	-0.118	0.017	0.349	-0.118	0.035
	[0.205]	[0.130]	[0.092]	[0.214]	[0.384]	[0.331]
40-49 year old	0.398*	-0.050	0.019	0.026	-0.399	0.557*
	[0.204]	[0.152]	[0.094]	[0.323]	[0.325]	[0.332]
50-59 year old	-0.193	-0.210***	-0.207***	-0.212	-0.669***	0.201
	[0.280]	[0.057]	[0.013]	[0.399]	[0.117]	[0.414]
New organizational practices						
Orga	0.106***	-0.021	0.009	0.075*	0.011	0.063
	[0.030]	[0.022]	[0.012]	[0.043]	[0.046]	[0.039]
Interaction effects (reference: *20-29 year old*)						
Orga x [30-39 year old]	-0.040	0.019	0.001	-0.037	-0.018	-0.035
	[0.037]	[0.026]	[0.015]	[0.050]	[0.054]	[0.045]
Orga x [40-49 year old]	-0.046	0.013	-0.005	-0.048	0.019	0.014
	[0.038]	[0.028]	[0.015]	[0.050]	[0.053]	[0.045]
Orga x [50-59 year old]	-0.047	0.100***	0.021	-0.033	-0.021	-0.053
	[0.048]	[0.034]	[0.018]	[0.054]	[0.062]	[0.050]
Computerization x age effects						
Comp	-0.018	0.075***	0.006	0.046	0.037	-0.012
	[0.034]	[0.025]	[0.014]	[0.040]	[0.049]	[0.043]
Interaction effects (reference: *20-29 year old*)						
Comp x [30-39 year old]	0.035	-0.039	-0.006	-0.018	0.038	0.035
	[0.040]	[0.030]	[0.017]	[0.047]	[0.057]	[0.048]
Comp x [40-49 year old]	0.018	-0.022	0.000	0.004	0.019	0.029
	[0.042]	[0.029]	[0.016]	[0.049]	[0.057]	[0.049]
Comp x [50-59 year old]	0.044	-0.144***	-0.039*	-0.019	0.021	0.048
	[0.052]	[0.038]	[0.020]	[0.059]	[0.066]	[0.054]
Controls for composition and selection effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2716	2704	2710	1667	1659	1654
p-value: no selection effect in training	0.75	0.25	0.10	0.94	0.56	0.75
log-likelihood	-1728	-1104	-522	-904	-1063	-814

Source: COI survey, employer section (SESSI, SCEES) and employee section (DARES), 1997; DADS panel, 1976–96.
Note: Probit models (marginal effects evaluated at sample mean). Standard errors are computed using the delta method. They are robust to cluster effects between workers of the same firm. Marginal effects are very similar when computed as the average of individual marginal effects over the sample. Controls for composition effects (tenure, education interacted with age group, firm size interacted with age group, frequency of early retirement in the industry, and plant's localization – rural) and selection effects (individual wage fixed effect, interacted with age group; attachment to employment indicator, interacted with age group; and indicator that a proxy has been imputed, interacted with age group).

TABLE 4: TRAINING PROFILES – ALTERNATIVE MEASURES
OF NEW ORGANIZATIONAL PRACTICES AND TECHNOLOGY

	Panel A: Clerks and blue-collar workers			**Panel B: Managers and technicians/supervisors**		
	Dependant variable: incidence of training...			Dependant variable: incidence of training...		
	... in the main task	... in computer skills	in teamwork	... in the main task	... in computer skills	in teamwork
	(3)	(3)	(3)	(3)	(3)	(3)
Age effects (ref. *20-29 year old)*						
30-39 year old	0.279	-0.138	0.061	0.431**	-0.205	-0.035
	[0.220]	[0.137]	[0.130]	[0.192]	[0.390]	[0.341]
40-49 year old	0.464**	-0.022	0.001	0.141	-0.483	0.528
	[0.208]	[0.170]	[0.093]	[0.309]	[0.310]	[0.373]
50-59 year old	-0.106	-0.157	-0.199***	-0.107	-0.640***	0.217
	[0.331]	[0.100]	[0.013]	[0.398]	[0.143]	[0.462]
New organizational practices						
Orga	0.020**	-0.001	0.005	0.019	0.013	0.009
	[0.008]	[0.006]	[0.003]	[0.013]	[0.014]	[0.012]
Interaction effects (reference: *20-29 year old*)						
Orga x [30-39 year old]	-0.006	0.006	-0.002	-0.014	-0.006	-0.003
	[0.010]	[0.008]	[0.004]	[0.015]	[0.017]	[0.013]
Orga x [40-49 year old]	-0.003	0.000	-0.003	-0.011	-0.006	0.012
	[0.011]	[0.008]	[0.004]	[0.015]	[0.016]	[0.013]
Orga x [50-59 year old]	-0.004	0.016	0.003	-0.002	-0.011	0.001
	[0.014]	[0.010]	[0.005]	[0.016]	[0.018]	[0.015]
Computerization x age effects						
Comp	0.107*	0.064	-0.002	0.099	0.025	0.142*
	[0.058]	[0.039]	[0.025]	[0.113]	[0.118]	[0.075]
Interaction effects (reference: *20-29 year old*)						
Comp x [30-39 year old]	0.014	0.030	-0.012	-0.099	0.128	0.058
	[0.077]	[0.067]	[0.026]	[0.139]	[0.149]	[0.170]
Comp x [40-49 year old]	-0.076	-0.009	0.066	-0.079	0.153	-0.097
	[0.077]	[0.061]	[0.056]	[0.126]	[0.135]	[0.125]
Comp x [50-59 year old]	-0.079	-0.096*	0.058	-0.114	-0.052	-0.077
	[0.104]	[0.053]	[0.082]	[0.138]	[0.147]	[0.127]
Controls for composition and selection effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2716	2704	2710	1667	1659	1654
log-likelihood	-1730	-1111	-520	-911	-1065	-811
p-value no selection effect in training	0.78	0.25	0.05	0.90	0.51	0.72

Source: COI survey, employer section (SESSI, SCEES) and employee section (DARES), 1997.
Note: Probit models (marginal effects evaluated at sample mean). Standard errors are computed using the delta method. They are robust to cluster effects between workers of the same firm. Marginal effects are very similar when computed as the average of individual marginal effects over the sample. Controls for composition effects (tenure, education interacted with age group, firm size interacted with age group, frequency of early retirement in the industry, and plant's localization – rural) and selection effects (individual wage fixed effect, interacted with age group; attachment to employment indicator, interacted with age group; and indicator that a proxy has been imputed, interacted with age). The measures of new organizational practices and computerization follow Aubert *et al.* [2006].

TABLE 5: COMPUTER USE AND COMPUTER TRAINING

	Panel A: Clerks and blue-collars					**Panel B: Managers and technicians/supervisors**				
	Nested logit: impact on the probability...			Probit model: impact on the incidence of...		Nested logit: impact on the probability...			Probit model: impact on the incidence of...	
	... of not using computer	... of using computer without training	... of using computer with training	... computer use	... computer training among computer users	... of not using computer	... of using computer without training	... of using computer with training	... computer use	... computer training among computer users
	(6)	(6)	(6)	(3)	(3)	(6)	(6)	(6)	(3)	(3)
New organizational practices x age effects										
Orga x [20-29 year old]	-0.028	0.049	-0.021	0.018	-0.073	-0.033	0.014	0.019	0.047	-0.019
	[0.025]	[0.026]*	[0.024]	[0.029]	[0.047]	[0.038]	[0.066]	[0.064]	[0.036]	[0.048]
Orga x [30-39 year old]	-0.039	0.041	-0.002	0.042	-0.045	-0.008	0.016	-0.008	0.007	-0.008
	[0.023]*	[0.017]**	[0.023]	[0.022]*	[0.034]	[0.029]	[0.038]	[0.043]	[0.021]	[0.030]
Orga x [40-49 year old]	-0.006	0.016	-0.010	0.006	-0.039	-0.015	-0.009	0.024	0.012	0.027
	[0.022]	[0.017]	[0.018]	[0.023]	[0.039]	[0.025]	[0.034]	[0.032]	[0.020]	[0.030]
Orga x [50-59 year old]	-0.092	0.007	0.085	0.093	0.099	-0.037	0.038	-0.001	0.026	-0.047
	[0.038]**	[0.03]	[0.032***	[0.038]**	[0.067]	[0.044]	[0.048]	[0.053]	[0.023]	[0.045]
Computerization x age effects										
Comp x [20-29 year old]	-0.101	0.025	0.076	0.115	0.087	-0.001	-0.040	0.042	0.010	0.035
	[0.034***	[0.031]	[0.029***	[0.034]***	[0.057]	[0.051]	[0.068]	[0.07]	[0.035]	[0.048]
Comp x [30-39 year old]	-0.072	0.039	0.034	0.078	0.008	-0.035	-0.028	0.063	0.046	0.057
	[0.025***	[0.021]*	[0.025]	[0.023]***	[0.038]	[0.023]	[0.04]	[0.04]	[0.022]**	[0.031]*
Comp x [40-49 year old]	-0.077	0.020	0.057	0.087	0.043	-0.062	0.021	0.042	0.073	0.011
	[0.03]**	[0.022]	[0.024]**	[0.024]***	[0.043]	[0.022***	[0.04]	[0.04]	[0.021]***	[0.033]
Comp x [50-59 year old]	0.036	0.015	-0.050	-0.041	-0.130	-0.063	0.031	0.032	0.043	0.035
	[0.037]	[0.036]	[0.034]	[0.040]	[0.078]*	[0.044]	[0.051]	[0.05]	[0.026]	[0.049]
Controls for selection and composition effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations		2704		2716	1005		1659		1660	1384
Log-likelihood		-727.2		-1547.1	-650.9		-504.1		-634.3	-878.0
p-value: effect of *Orga* identical at *40-49* and *50-59*	**0.048**	0.798	**0.010**	**0.048**	0.066	0.665	0.421	0.684	0.649	0.171
p-value: effect of *Comp* identical at *40-49* and *50-59*	**0.018**	0.893	**0.010**	**0.005**	**0.045**	0.981	0.871	0.884	0.393	0.685

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Source: COI survey, employer section (SESSI, SCEES) and employee section (DARES), 1997.
Note: Nested logit models (average predicted impacts of a 1 standard-deviation increase in the *Orga* and *Comp* variables, standard errors computed by bootstrap) and probit models (marginal effects evaluated at sample mean). Controls for composition effects (age group, tenure, education interacted with age group, firm size interacted with age group, frequency of early retirement in the industry, and plant's localization – rural) and selection effects (individual wage fixed effect, interacted with age group; attachment to employment indicator, interacted with age group; and indicator that a proxy has been imputed, interacted with age).

TABLE A1: DESCRIPTIVE STATISTICS

Panel A: Within age group breakdowns according to training incidence, education level and firm size

		Subsample with more frequent use...	
	Whole sample	... of new organizational practices	... of new technologies
Incidence of training in the main task			
20-29 year-old	0.54	0.65	0.62
30-39 year-old	0.56	0.65	0.64
40-49 year-old	0.55	0.64	0.64
50-59 year-old	0.50	0.60	0.62
Incidence of training in computer skills			
20-29 year-old	0.26	0.32	0.34
30-39 year-old	0.31	0.38	0.41
40-49 year-old	0.32	0.38	0.41
50-59 year-old	0.30	0.39	0.40
Incidence of training in teamwork			
20-29 year-old	0.08	0.11	0.11
30-39 year-old	0.10	0.14	0.13
40-49 year-old	0.14	0.19	0.17
50-59 year-old	0.16	0.20	0.21
Education level			
College			
20-29 year-old	0.49	0.52	0.56
30-39 year-old	0.32	0.38	0.39
40-49 year-old	0.24	0.28	0.28
50-59 year-old	0.22	0.22	0.24
High-school			
20-29 year-old	0.39	0.39	0.35
30-39 year-old	0.48	0.46	0.47
40-49 year-old	0.41	0.41	0.41
50-59 year-old	0.34	0.36	0.35
High-school dropouts			
20-29 year-old	0.12	0.08	0.08
30-39 year-old	0.19	0.16	0.14
40-49 year-old	0.35	0.32	0.31
50-59 year-old	0.44	0.42	0.41
Firm size			
50-199 workers			
20-29 year-old	0.46	0.24	0.18
30-39 year-old	0.43	0.21	0.18
40-49 year-old	0.38	0.16	0.14
50-59 year-old	0.34	0.12	0.09
200-999 workers			
20-29 year-old	0.41	0.52	0.56
30-39 year-old	0.43	0.53	0.54
40-49 year-old	0.45	0.57	0.56
50-59 year-old	0.46	0.54	0.57
>1000 workers			
20-29 year-old	0.13	0.23	0.26
30-39 year-old	0.14	0.26	0.28
40-49 year-old	0.17	0.28	0.30
50-59 year-old	0.20	0.33	0.35
Tenure (in years)	14.02	14.48	14.76
Rural dummy	0.28	0.24	0.23
Number of observations	4383	2176	2146

Source: COI survey, employer section (SESSI, SCEES) and employee section (DARES), 1997.
Note: Coefficients are sample average over the whole sample or over the sub-sample of workers in firms with more frequent use of new organizational practices / new technologies (i.e. with positive values of *Orga* and *Comp*, respectively).

TABLE A1 (CONTINUED)

Panel B: Correlation coefficients

	Age	Use of new organizational practices (Orga)	Use of new technologies (Tech)	Organizational change	Technical change
Managers and technicians/supervisors					
Age	1	-0.0309	-0.0129	-0.0221	-0.0174
Incidence of training in the main task	-0.0454	0.2030*	0.2068*	0.1076*	0.1021*
Incidence of training in computer skills	-0.002	0.1457*	0.1939*	0.0891*	0.0941*
Incidence of training in teamwork	0.1216*	0.1671*	0.1491*	0.1658*	0.0597*
Clerks and blue-collars					
Age	1	0.0571*	0.0542*	0.0226	0.0155
Incidence of training in the main task	-0.0784*	0.2050*	0.1705*	0.1395*	0.0856*
Incidence of training in computer skills	-0.0131	0.1308*	0.1770*	0.0734*	0.0977*
Incidence of training in teamwork	0.0225	0.0905*	0.0757*	0.0653*	0.0236

* Significant at 5%

Source: COI survey, employer section (SESSI, SCEES) and employee section (DARES), 1997.
Note: Correlation coefficients over the whole sample.

TABLE A2: COMPUTERIZATION IN THE FIRM QUESTIONNAIRE

Computerization:

	Does your company outsource any of the following tasks? (OUT)	In 1997		Change since 1994		
3.9	*Telephony/networks*					
3.10	IT					

Are/were your company's management and production departments equipped with the following IT resources ?

		MANAGEMENT		PRODUCTION	
		1997	1994	1997	1994
16.1	Mainframe computer				
16.2	Non-Networked microcomputer				
16.3	Networked microcomputer				

Has your company used, or does it use IT interfaces (computer network, EDI links, etc.) for data transfers ?

		1997		1994	
		Yes	No	Yes	No
19.1	within management departments (purchasing, sales, marketing, accounting etc.)				
19.2	between management and production departments (process engineering, production management, manufacturing etc.)				
19.3	between management and suppliers, subcontractors or service providers				
19.4	between management and corporate clients				
19.5	between management and social organizations, public authorities				
19.6	between design departments (research, development and design) and production				
19.7	between design departments and suppliers, subcontractors or service providers				
19.8	within production departments or between manufacturing units				
19.9	between production departments and suppliers, subcontractors or service providers				
19.10	between production departments and corporate clients				

	Did your company use Internet for any of the following in 1997 ?	Yes	No
20.1	Accessing e-mail		
20.2	Disseminating information (e.g. Web pages)		
20.3	Searching for information		

TABLE A3 : ORGANIZATIONAL PRACTICES IN THE FIRM QUESTIONNAIRE

New organizational practices:

Does your company outsource any of the following tasks? (OUT)		In 1997		Change since 1994		
		Yes	No	+	=	-
3.1	Research/development/design					
3.2	Purchasing					
3.3	Production engineering/production management/scheduling					
3.4	Manufacturing/production					
3.5	Quality assurance					
3.6	Maintenance					
3.7	Sales					
3.8	Marketing/advertising					
3.11	Human resources/staff training					
3.12	Accounting/management control					
3.13	Finance/cash management					
3.14	Legal affairs					
3.15	Environment/health and safety					

Does your company use the following organizational device?		In 1997		Change in the % of employees affected since 1994		
		Yes	No	+	=	-
4.1	ISO 9001, ISO 9002, EAQF certification					
4.2	Other certification or total quality management					
4.3	Value analysis, functional analysis or “AMDEC” method					
4.4	5S method or TPM (Total Productive Maintenance)					
4.5	Organization in profit centers					
4.6	Formal in-house customer/supplier contracts					
4.7	System of just-in-time delivery					
4.8	System of just-in-time production					

In general, who is/was authorized to do the following in your company workshops? (more than one answer possible)		In 1997			In 1994		
		Management (MAN)	Production worker (PW)	Specialist (SPE)	Management (MAN)	Production worker (PW)	Specialist (SPE)
6.1	Adjust installations						
6.2	Perform 1st level maintenance						
6.3	Allocate tasks to production workers						
6.4	Inspect quality of supplies						
6.5	Inspect quality of production						
6.6	Participate in performance improvements						
6.7	Participate in project teams						
6.8	Stop production in case of an incident						
6.9	Troubleshoot in case of an incident						
6.10	Start production again in case of an incident						

7. How many hierarchical layers are/were there between production workers (level 0) and the head of the company (level N)? (HL) and (EVHL)			
In 1997		In 1994	

TABLE A4: CONSTRUCTION OF *COMP* VARIABLE

%	1994	1997	Weights
Equipment characteristics			
Mainframe computer in management activities	54	59	0.146
Mainframe computer in production activities	40	47	0.157
Non networked PCs in management activities	48	46	-0.012
Non networked PCs in production activities	34	36	0.027
Networked PCs in management activities	31	66	0.142
Networked PCs in production activities	22	49	0.150
Intensity of computer data transfers			
No within firm transfers	54	30	0
Intense within firm transfers	7	16	0.291
No transfers with suppliers or subcontractors	89	73	0
Intense transfers with suppliers or subcontractors	2	6	0.182
No transfers with corporate clients	86	66	0
Intense transfers with corporate clients	3	10	0.228
Transfers with public authorities	11	22	0.115
Internet use			
No use of Internet	100*	60	0
Complex use of Internet	0*	13	0.194
Organization of IT function			
Full time IT manager	25	45	0.192
Outsourcing of IT activities	24*	40	0.026
Full time phone and network manager	6	13	0.206
Outsourcing of phone and network activities	22*	31	0.038

Source: COI survey, employer section (SESSI and SCEES), 1997.

Note: This table gives the percents computed on the sample of 3286 manufacturing firms with more than 50 employees in 1994 and 1997. * Indicates that the figure has been estimated. The first column gives the number of items per discrete variables, while the last column gives the weights used to compute the synthetic 1994 and 1997 variable measuring the intensity in IT use.

TABLE A5: CONSTRUCTION OF *ORGA* VARIABLE

%	1994	1997	Weights
Quality			
ISO 9001, ISO 9002 or EAQF certification	19*	49	0.154
Other certification or Total Quality Management	15*	35	0.123
Value analysis, functional analysis or AMDEC method	14*	26	0.197
Just in time			
System of just in time delivery	21*	39	0.166
System of just in time production	20*	38	0.158
5S method or Total Productive Maintenance	7*	16	0.204
Market devices			
Organization in profit centres	20*	31	0.134
Formal in-house customer / supplier contracts	16*	29	0.133
Outsourcing of more than 3 tasks	33*	47	0.053
Subcontracting of production	36*	54	0.044
Employee implication			
High implication of production workers (7 to 10 tasks)	14	22	0.183
High implication of specialists (7 to 10 tasks)	17	18	0.171
Low implication of management (0 to 3 tasks)	18	20	0
High implication of management (8 to 10 tasks)	27	24	-0.001
Structure			
From 0 to 2 departments / divisions	35	15	0
9 and more departments / divisions	15	36	0.207
From 0 to 2 hierarchical layers	27	28	0
From 5 and 9 hierarchical layers	21	17	0.168

Source: COI survey, employer section (SESSI and SCEES), 1997.
Note: This table gives the percents computed on the sample of 3286 manufacturing firms with more than 50 employees in 1994 and 1997. * Indicates that the figure has been estimated. The first column gives the number of items per discrete variables, and the last column gives the weights used to compute the synthetic 1994 and 1997 variable measuring the intensity in use of new organizational practices.