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Training and Age-Biased Technical Change : Evidence from French Micro Data

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Training and Age-Biased Technical Change : Evidence from French Micro Data[1]

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Abstract

We model and test the hypothesis that technical and organizational change may be biased against older workers. This may occur through a direct adverse effect on their productivity, or through insufficient training responses to change. We show that the impact of technical and organizational change on the optimal training profile and on the age of retirement is theoretically indeterminate. Using a French matched employer-employee data set, we find evidence that computerized firms select their older workers more. But modern firms also tend to train all their workers more, regardless of age. Technical change may thus explain a decline in the employment of older workers through a direct unfavorable impact on their productivity rather than through a comparative disadvantage with regard to training.

Classification: J14, J24, J26, O30
Keywords: Technical change; organizational change; training; older workers; early exit

Résumé

Nous modélisons et testons l'hypothèse selon lequel le changement technologique et organisationnel aurait des effets asymétriques sur les différentes classes d'âge de travailleurs.

Un modèle théorique simple permet de montrer que l'effet net du changement technologique sur l'emploi et la formation des seniors est indéterminé, dans la mesure où l'entreprise et le travailleur peuvent répondre aux effets défavorables du changement par un investissement de formation accru et mieux réparti sur toute la carrière du salarié.

Cet effet net est ensuite estimé sur données microéconomiques françaises appariées (données au niveau du poste de travail et de l'entreprise). L'effet sur l'emploi semble défavorable aux seniors : les entreprises plus informatisées sélectionnent plus fortement leurs travailleurs âgés. Mais les travailleurs âgés ne semblent pas souffrir d'un désavantage comparatif par rapport à la formation : les entreprises plus modernes (en termes de technologie et d'informatisation) tendent à former davantage tous leurs salariés, y compris les seniors. Le changement technologique permet donc d'expliquer une baisse de l'emploi des seniors par son effet direct défavorable sur leur productivité plutôt que par l'insuffisance de leur investissement de formation.

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INTRODUCTION

In 2002, 42% of men and 54% of women aged 55 to 59 were either unemployed or out of the labor force in France, whereas the legal age of retirement was 60. Though these low employment rates are below the OECD average, similar ones are not uncommon in continental Europe, and the ageing workforce calls for an increase in the employment of older workers in all OECD countries. However, in a context of rapid technical and organizational change, a major obstacle may be that the employment prospects of older workers are currently limited by accelerated skill obsolescence.[1]

By contrast with the skill-biased technical change (SBTC) hypothesis, the idea that technological and organizational change may have asymmetric effects with regard to age (an age-biased technical – and organizational – change, or ABTC) has received limited attention. The first investigations have taken three approaches and yielded contrasted results.

First, several papers have asked whether older workers are slower to adopt innovating tools – such as computers. Overall, they find evidence of a slow decline in adoption with age. Friedberg (2003) shows that successive cohorts of workers in the United States adopted computers at all ages, with a slight slowdown only for workers close to retirement – which she interprets as the effect of a shorter payback period rather than as a difficulty due to age. Weinberg (2004) shows that this average slight slowdown actually covers sharp contrasts between high school graduates, whose computer use actually increases with experience, and college graduates who adopt computers more at the beginning of their career. His interpretation is that less educated workers' experience helped them use the new technology, whereas young educated workers relied upon formal schooling. The picture is completed by Koning and Gelderblom (2004) who show, using Dutch data, that even though the share of workers using computers slowly falls with age, the number and the complexity of tasks performed on computers also declines.[2] One key limit of this literature is that it may suffer from selection

[1] Rosen (1975) initiated the economic analysis of skill obsolescence. For a recent review, see De Grip and Van Loo (2002).

[2] The results by Friedberg (2003) and Weinberg (2004) are based on the Current Population Survey (CPS), which contained data on computer use in 1984, 1989, 1993 and 1997. Frieberg's main purpose is to test the impact of computer adoption on the age of retirement; using an instrumental variable approach, she finds that older workers adopting computers retire later.

bias, if those older workers who were the least likely to adopt new tools have left the labor force.

This issue is addressed by a second strand of literature, that focuses on the effects of technological and organizational change 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 the workers have not received training in time.[3] Using French firm data, Aubert, Caroli and Roger (2004) estimate the impact of technology and organization 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. Not only do these firms dismiss older workers more frequently, but they also tend to hire a smaller proportion of them.[4]

A last strand of literature looks at the failures to adopt new technologies through costs of adoption for people of different age. Different categories of employees may resist to the implementation of an innovation available for the management but that makes them worse off. Canton, de Groot and Nahuis (2002), Bellettini and Ottaviano (2005) model this resistance using models of vested interests with overlapping generations. Competing generations, responding to economic motives invest resources to lobby either for the maintenance of the current technology or for the adoption of a new one. Diaye et al. (2004) test a model in which the demographic structure of the firm has an influence on the propensity to adopt technological or organizational change. They show that firms in which senior employees are more numerous than young and intermediate age employees are less likely to adopt innovations.

Koning and Gelderblom (2004) use a survey of 538 workers in the printing industry and in wholesale trade. They show that using computers positively affects performance, as measured by the worker's perceived change in his performance and by periodical job performance interviews.

[3] Earlier results by Mincer (1988), though they do not focus on a specific age group, are consistent with this explanation: in the short run, firms seem to adjust to a more rapid pace of technical change by hiring workers with higher education; in the long run, though, skill adjustment is obtained by training the workers in the firm.

[4] This proves that older workers do not only bear a disproportionate share of the adjustment (downsizing) that often accompanies organizational change, as they are eligible for public early-retirement schemes. There seems to be a decrease in the demand for older workers per se.

Overall, this emerging body of literature brings some evidence in favor of the ABTC hypothesis. Nonetheless, computer adoption does not decline dramatically nor systematically with age. Moreover, the effects of technical change on the employment of older workers may be positive in the long run. This mixed picture may partly stem from the estimations' limits (selection bias, limited sources of variation, endogeneity issues). It may also reflect the fact that the impact of the changes on older workers is conditioned by the actions taken by firms and workers to accompany the changes – actions that may vary across time and countries. In particular, training decisions along workers' career are likely to play a decisive role. Not surprisingly, training choices underlie the interpretation of the results in many of the above papers.[5] But these training decisions are neither formally modelled nor directly measured.

The present paper aims at filling this gap by putting training decisions along workers' career at the core of the analysis: Does organizational and technical change have an asymmetric impact on younger and older workers, taking into account the training responses of workers? A striking stylized fact further motivates the focus on training: the dramatic rise in training incidence in the the late eighties in France[6], which was accompanied by a relative decline for older workers (figure 1[7]). Interpreting training as a response to organizational and technical change along the workers' career may help explain these evolutions.

Distinguishing a direct effect on the productivity of older workers from an indirect effect through training, we first show that the impact of technological and organizational change on the optimal amount of training received by older workers and on their retirement decision is theoretically indeterminate. This is in particular due to the opposite effects of skills depreciation and schooling obsolescence, on the one hand, and of increased returns to training on the other hand.

We assess these effects empirically using a unique data source that enables us to consistently measure training (at the worker level), technical and organizational change (at the firm level) as well as individual productive characteristics

[5] See in particular Bartel and Sicherman (1993), Friedberg (2003), and Aubert et al. (2004).

[6] A period of accelerated technical and organizational change in France; see Greenan (2003).

[7] Figure 1 depicts the evolution of training incidence from a worker survey (the 'Formation et qualification professionnelle' survey in years 1977, 1985 and 1993). The period considered by each survey is a five year period: 1972-77, 1980-85, 1988-93. Access rates are predicted from a probit model, net of composition effects in the following dimensions: occupation, industry, firm size, education and sex of the worker. See Behaghel (2002) for more details.

of the worker. There are two key empirical results: First, older workers in more computerized firms are highly selected – consistently with the view that employers and older workers negatively affected by modernization find it mutually advantageous to separate, or that firms with a higher proportion of older workers are less likely to adopt new technologies. Second, modern firms train their workers more, at all ages, and there is no evidence that they discriminate against their older workers with regard to training, except for computer training.

These results complement those of Bartel and Sicherman (1993) and Friedberg (2003): they provide direct evidence that firms and workers respond to computerization and organizational change by training, even at the end of workers' careers. Furthermore, they shed light on the mechanism that underlies the findings of Aubert et al. (2004): the decrease in the relative demand for older workers must be mostly due to a direct effect of computerization and organizational change on the productivity of older workers, as opposed to an indirect effect that would be due to their inability to adapt to changes through training.

The paper proceeds as follows. A theoretical model analyzes the effects of technical and organizational change on training and retirement in section 1. Section 2 details the empirical strategy to estimate these effects. The results are given in section 3 and section 4 concludes.

I. A MODEL OF AGE-BIASED TECHNICAL CHANGE

We first need to make clear what we tentatively call 'age-biased technical change', and how it relates to but differentiates from skill-biased technical change.[8] Skills and age are correlated, as some skills are accumulated with work experience. However, age has specific effects that go beyond what is usually defined as skill-biased technical change. First, the mix of skills accumulated (learning skills vs.

[8] There is a risk otherwise that a "biased" change be a "black box". As Bresnahan et al. (2002) put it, "Skill-biased technical change (SBTC) means technical progress that shifts demand toward more highly skilled workers relative to the less skilled. It also tends to be something of a residual concept, whose operational meaning is often 'labor demand shifts with invisible causes'." (p.267). Among the attempts to open the black box, Autor, Levy and Murnane [2003] analyze the complementarity of computers with different types of tasks (routine and nonroutine), which in turn imply different skill levels of the workforce. On the SBTC literature, see Autor and Katz (1999), Card and DiNardo (2002) and Acemoglu (2002).

productive skills, specific vs; general skills, analytical vs. interactive skills,...) depends on age. Second, vintage effects intervene. Third, training opportunities are affected by age. We present a simple theoretical model to clarify these age effects that explain why technical change may have an asymmetric effect on workers of different ages, and to provide a framework for the empirical analysis. The model focuses upon the consequences on two dimensions of the workers' career: the training and retirement decisions.[9]

Consider a two-period model of a worker's career. In period 1, the worker is considered as a "younger worker", and in period 2, as an "older worker". There is one representative firm, to which the worker is already matched at the beginning of period 1. The job is always mutually profitable in period 1. The firm and the worker have two key decisions to take: whether or not to separate at period 2, when the worker may be entitled to social security early-retirement benefits and the value of leisure is presumably higher; and which level of training T_1 (respectively T_2) to choose at the beginning of period 1 (respectively at the beginning of period 2, if the job is not destroyed).

There is no uncertainty. We assume that separation decisions are efficient: the job is destroyed if and only if the surplus it generates is negative. The outside options of the worker and the firm, if the job is destroyed, are early-retirement benefits, the value of leisure and the firm's value of a vacancy; they are taken as exogenous and their sum yields R_2. Thus, early retirement takes place when the product of the job in period 2, net of training costs, is lower than R_2. We also assume privately efficient training decisions: the amount of training is chosen to maximize the joint surplus of the firm and the worker. Of course, it may be interesting to consider different assumptions with inefficient training and separation decisions, for instance due to assymmetric information or 'poaching' issues.[10] However, a benchmark with efficient decisions seems a natural starting point; it turns out that the impact of technical change in that setting is indeterminate; more complex assumptions would probably reinforce that point.

We first derive the expression of optimal training and separation decisions, then examine the direct and indirect effects of technical change on these decisions, before concluding on the net effect.

[9] Technical and organizational change remains exogenous. The empirical problems raised by the endogeneity of technical and organizational change are developed in the next section.

[10] Poaching may not occur here as we only consider one firm; this simplifying assumption also puts aside the distinction between specific and general human capital.

I.A Optimal training and separation decisions

As there is no uncertainty, the firm and the worker know *ex ante* whether the job will last over the two periods. First consider the case of a worker that will stay in the firm for the two periods. The surplus generated by her job is:

$$\begin{aligned} S &= y_1 + a + rT_1 - C(T_1, a, E) - R_1 \\ &\quad + \beta \left[y_2 + a + r(\lambda_1 T_1 + T_2) - C(T_2, a, \lambda_e E) - R_2 \right] \end{aligned}$$

The first line details the surplus generated in period 1, S_1, and the second line the surplus in period 2, discounted by β ($\beta < 1$).

$y_1 + a + rT_1$ is the product of a job in period 1. The first component y_1 is common to all younger workers.[11] a is a fixed, individual-specific term that represents the worker's ability. rT_1 is the productive return to training T_1. $C(T_1, a, E)$ is the total cost of training: it depends on a (as more able workers find it easier to train) and on education E (as more educated workers have learning skills that help them acquire productive skills). More specifically, assume that training costs are increasing and convex in T_t, and that the marginal cost of training decreases with a and E:

$$\frac{\partial C}{\partial T_t} > 0, \quad \frac{\partial^2 C}{\partial T_t^2} > 0, \quad \frac{\partial C}{\partial a} < 0, \quad \frac{\partial C}{\partial E} < 0, \quad \frac{\partial^2 C}{\partial T_t \partial a} < 0, \quad \frac{\partial^2 C}{\partial T_t \partial E} < 0$$

The expression of the surplus in period 2 is very similar. However, productive skills acquired in period 1 have depreciated; they are discounted by λ_1 (with $\lambda_1 < 1$). Moreover, learning skills from schooling are partly obsolete: E is discounted by λ_e ($\lambda_e < 1$).[12]

First consider the levels of training T_1^* and T_2^* chosen, conditional on the fact that the job is not destroyed in period 2. Maximizing S with regard to T_1 and T_2 yields the first-order conditions for an interior solution

$$\frac{\partial C(T_1, a, E)}{\partial T_1} = r(1 + \beta \lambda_1) \tag{1}$$

$$\frac{\partial C(T_2, a, \lambda_e E)}{\partial T_2} = r \tag{2}$$

[11] More generally, y_1 may depend on E if education does not only provide learning skills but also productive skills. The extension is straightforward.

[12] Note that the terminology used differs from Rosen (1975). Here, 'depreciation' refers to a loss in productive skills acquired from training and 'obsolescence' to a loss in learning skills acquired from schooling.

These equations implicitely define the optimal amounts of training $T_1^*(a,E,r,\lambda_1)$ and $T_e^*(a,E,r,\lambda_e)$. By differentiating equations 1 and 2, and using assumptions on partial derivatives of C, one shows that

$$\begin{array}{llll} \frac{\partial T_1^*}{\partial a} > 0, & \frac{\partial T_1^*}{\partial E} > 0, & \frac{\partial T_1^*}{\partial r} > 0, & \frac{\partial T_1^*}{\partial \lambda_1} > 0 \\ \frac{\partial T_2^*}{\partial a} > 0, & \frac{\partial T_2^*}{\partial E} > 0, & \frac{\partial T_2^*}{\partial r} > 0, & \frac{\partial T_2^*}{\partial \lambda_e} > 0 \end{array}$$

$T_1^*(a,E,r,\lambda_1)$ and $T_e^*(a,E,r,\lambda_e)$ are consistent training decisions if and only if the job actually lasts for two periods. This is the case when the surplus generated in period 2 is positive, i.e. $S_2^*(a) \geq 0$ where

$$(3) \quad S_2^*(a) = y_2 - R_2 + a + r\lambda_1 T_1^*(-) + \max_{T_2}\left[rT_2 - C(T_2, a, \lambda_e E)\right]$$

$S_2^*(a)$ is strictly increasing in a. Indeed, using the envelop theorem,

$$\frac{\partial S_2^*(a)}{a} = 1 + r\lambda_1 \frac{\partial T_1^*}{\partial a} - \frac{\partial C(T_2^*, a, \lambda_e E)}{\partial a}$$

Each term of the right-hand side is positive, so that $\frac{\partial S_2^*(a)}{a} > 0$. Provided that a covers a sufficient range of values, there is a unique value a^*, implicitely defined by $S_2^*(a^*) = 0$, such that $S_2^*(a) \geq 0 \iff a \geq a^*$.

Second, consider the case of a worker such that $S_2^*(a) < 0$. It is inefficient that she remain employed in period 2. But, anticipating this early-retirement decision, the firm and the worker adjust the level of training in period 1 to take into account the shorter payback period. T_1 is chosen to maximize $S_1 = y_1 + a + rT_1 - R_1 - C(T_1, a, E)$; the first-order condition for an interior solution yields

$$\frac{\partial C(T_1, a, E)}{\partial T_1} = r$$

This implicitely defines $\widetilde{T_1}(a,E,r)$.[13] Noting that $\widetilde{T_1}(a,E,r) = T_1^*(a,E,r,0)$ with $\frac{\partial C(T_1^*, a, E, \lambda_1)}{\partial \lambda_1} > 0$ proves that $\widetilde{T_1}(a,E,r) < T_1^*(a,E,r,\lambda_1)$ for any $\lambda_1 > 0$.

To summarize, workers with sufficient ability ($a > a^*$) stay in the firm for the two periods and receive training T_1^* and T_2^*. Workers with lower ability retire

[13] We assume that the job is never destroyed in period 1. This holds if $y_1 - R_1$ is sufficiently large so that for any a, $S_1^*(a) = y_1 + a + r\widetilde{T_1}(a,E,r) - R_1 - C(\widetilde{T_1}(a,E,r), a, E) \geq 0$.

early (after period 1); consequently, they receive a lower amount of training $\widetilde{T_1}$ in period 1.

What are, in that simple setting, the consequences of technical and organizational change?

I.B The direct effect of technical change through productivity

Technical and organizational change may first affect the productivity of older workers y_2 directly, i.e. independently from training. Specifically, it is often argued that the relative productivity of older workers should decrease. One can distinguish three main arguments.

First, change per se may be unfavorable to older workers, if they are more productive in a stable environment. Strikingly, 42% of a sample of French managers consider that an ageing workforce will have negative effects on the introduction of new technologies.[14] Older workers themselves often declare more difficulties in the use of information and communication technologies (Koning and Gelderblom, 2004). Do these negative opinions find empirical support? The fact that older workers have more difficulty coping with changes receives some support from case studies (Brynjolfsson, Renshaw and Van Alstyne, 1997) and from the ergonomic literature: more frequent job rotation hinders the strategies of older workers who build on their experience to compensate for decreasing physical strength or intellectual reactivity (Jolivet et al., 2000).

Second, the content of the changes may be unfavorable to older workers. In particular, in the nineties, firms have implemented new sets of managerial tools that common and strongest impact on work characteristics is an increase in the intensity of communication (Caroli, 2001), for which older workers may be at a disadvantage, either as an effect of generation or as an effect of age (see Alexandre-Bailly et al., 2004, for case study evidence).

Finally, technological and organizational change may induce a depreciation of human capital acquired on the job, affecting in particular older workers with more experience and longer tenure in their firm. There are several ways in which this depreciation of human capital may occur. First, the new technologies of information and communication may change the way in which “knowledge” is stored within firms. In traditional firms, older workers act as informal mem-

[14] This is the most frequently perceived negative consequence of the ageing workforce, with higher labor costs (41% of responding managers). See Monso and Tomasini (2003).

ory of the firm. But in new organizations, the knowledge may be more easily codified and distributed through information systems (Caroli, 2003). Second, new models of value creation ("post-fordism") may value seniority less as it is precisely the rapid recombination of talented workers and capital that creates value (DiPrete, Goux and Maurin, 2002).

The decrease in the productivity of older workers is modelled as a fall in y_2. This reduces the surplus in period 2, $S_2^*(a)$ and leads more workers to retire early (the threshold a^* increases).[15] It has composition effects on training: some workers who were to work for two periods now only work for one. Facing a shorter payback period, they train less in period 1. Consequently, the average level of training among younger workers decreases. Also, the average ability of older workers still employed in period 2 increases; if more able workers have a higher propensity to train, the average level of training observed among older workers increases.

I.C The indirect effect of technical change through training

Technical and organizational change also impacts training decisions through three distinct channels.

First, technical and organizational change increases the return on training investments r, under the assumption that human capital and technology (respectively innovative organization) are complementary. This induces higher training investments. It also has employment effects: the surplus in period 2, $S_2^*(a)$, increases, making it worthwhile for less able workers to delay retirement up to the end of period 2.

Second, the changes may accelerate the obsolescence of the learning skills of older workers, as they were acquired at school a longer time ago – when there were no computers and when teachers focused less on oral communication skills, for example. A typical case concerns older architects, for whom learning new computerized techniques has become too costly (MacDonald and Weisbach, 2001). This fall in λ_e increases training costs for older workers, resulting in a reduction in training T_2^*. It also induces a larger share of older workers to retire early.

Third, the changes increase the rate at which productive skills T_1 depreciate. This decrease in λ_1 reduces the total return to T_1 for workers expecting to remain

[15] Differentiating equation 3 with regard to a^* and y_2 yields $\frac{da^*}{dy_2} = -\frac{1}{\partial S_2^*/\partial a} < 0$

employed in period 2. Therefore, T_1^* falls. It also leads to more frequent early retirement decisions.[16]

In the same way as with the direct effect, changes in early retirement decisions have secondary effects on the average amount of training observed in each age group, through composition effects. For instance, the accelerated depreciation of training as well as the obsolescence of education induce more frequent early retirement decisions. This modifies the share of younger workers training only for one period; as they train less, the average amount of training observed among younger workers is reduced. By contrast, in period 2, selective departure of the less able older workers increases the average level of training, under the assumption that more able workers have a higher propensity to train. Conversely, the increased return to training delays retirement; it therefore has the opposite composition effects on the average amount of training observed among younger and older workers.

I.D Net effect

Table 1 summarizes the various effects of technical and organizational change: the direct effect (column 1) and the three channels of the indirect effect (columns 2 to 4). The first three rows describe the effects on training, conditional on age and on early-retirement decision. The next row describes the impact on the share of older workers retiring early. Eventually, the last two rows describe the effects on the average amount of training, taking all the workers of a given age group together, i.e. taking into account the impact on training for workers of a given ability as well as composition effects.

The first lesson of table 1 is that the net impact of technical and organizational change on training and employment decisions is *a priori* indeterminate. Concerning training, the indetermination is due to the opposition between the unfavorable effects of accelerated skills depreciation and increased schooling ob-

[16] The proof of the effect of each channel on retirement decisions, taking into account endogenous training responses, directely derives from equation 3. Differentiating with regard to a^* and λ_1 (respectively λ_e and r) yields:

$$\begin{aligned}
\frac{da^*}{d\lambda_1} &= -\frac{rT_1^* + r\lambda_1\left(\partial T_1^*/\partial \lambda_1\right)}{\partial S_2^*/\partial a} < 0 \\
\frac{da^*}{d\lambda_e} &= \frac{\partial C/\partial \lambda_e}{\partial S_2^*/\partial a} < 0 \\
\frac{da^*}{dr} &= -\frac{\lambda_1 T_1^* + r\lambda_1\left(\partial T_1^*/\partial r\right) + T_2^* + r\left(\partial T_2^*/\partial r\right)}{\partial S_2^*/\partial a} < 0
\end{aligned}$$

solescence, on one hand, and the favorable effect of increased returns to skills, on the other hand. Interestingly, this indetermination contrasts with earlier predictions in the literature: in an informal discussion, Bartel and Sicherman (1993) predicted increased training at all ages, and a stronger increase for older workers. But this prediction was based on faster skills depreciation combined with higher returns to skills; it did not consider the possible impact of schooling obsolescence. As for employment, the direct effect on productivity (combined with the obsolescence and accelerated depreciation effects) may be offset by increased returns to training. Overall, there are good theoretical reasons to believe that technical and organizational change has a differentiated impact on older workers, but the direction of that bias is unclear.

The second lesson of table 1 concerns the empirical analysis. A natural idea is to try to disentangle the direct and the indirect effects by analyzing jointly training and employment.[17] However, the difficulty comes from composition effects. For instance, even if only the direct effect is at play, the average observed training profile will be modified (see last two rows of column 1); but it would be a mistake to attribute these changes to the indirect effect. Controlling for individual ability a is necessary to estimate the indirect effect. This leads to the presentation of the empirical strategy.

II. EMPIRICAL STRATEGY

As training is the missing element in existing work on ABTC, and as effects on training profiles are *a priori* indeterminate, the core of our empirical strategy is to test whether technical and organizational change reduces training investments among older workers. However, the direct effect of technical and organizational change is also of interest, and it causes composition effects that must be controlled for to analyze the training profiles. Our strategy is therefore twofold: measure the effects of technical and organizational change on the selection of workers within firms, and then measure the impact of technical and organizational change on training profiles, controlling for that selection. We detail the

[17] A more ambitious goal would be to disentangle the increased obsolescence of education from the accelerated depreciation of productive skills, as they have opposite predicted effects on the relative access of older workers to training. However, it is difficult to construct separate measures of education obsolescence and of productive skills depreciation. Our attempts in that direction did not yield consistent results.

two steps of this approach after describing the data.

II.A The data

The data usually used in the literature does not allow to measure simultaneously access to training across ages and technological change in a satisfactory way.[18] A virtue of the data we use is to provide good measures of training (at the worker level) and of technological and organizational change (at the firm level). It also provides indirect measures of the workers' ability, a.

The data comes from a French survey on organizational change and computerization ("Changements Organisationels et Informatisation", COI), conducted at the end of 1997. It is a matched employer-employee survey. We work with a random sample of about 2500 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 (2 or 3) 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 (at the date of the survey) and on training. This yields a sample of about 4500 employees.[19]

The worker survey allows to measure the incidence of four types of training: training in the main task, training in computer skills, in management and in teamwork. Questions on these four types of training (see appendix A) were independent and will be considered separately. A fifth type of training (training in the use of automated machines) concerns fewer workers; the results for that type of training were less significant and are not reported here. Table 2 displays descriptive statistics on access to training for different groups of workers. Figure 2 displays the the incidence of each type of training according to age, net of composition effects (with 95% confidence intervals). Composition effects are taken into account by estimating a probit model that controls for firm size (three categories), industry (four categories[20]), education (three categories) and sex of the worker. These profiles are quite contrasted. Computer training and training

[18] This may help explain why training is not at the core of the empirical analysis in the emerging ABTC literature.

[19] The survey benefited from high response rates both on the firms' side (82%) and on the employees' side (71%). See appendix A for more details on the data.

[20] Remember that all firms come from the manufacturing sector. The four groups of industry we use correspond to a classification of the technological intensity of the industry based on the share of R&D expenditures in the value added.

in the main task are the most frequent. They display the usual inverse U shape, whereas access to training in teamwork and management increases continuously with age.[21] There is one issue with the measurement of access to training in the COI data: the question does not systematically specify the period in which the training session has occurred. The observation period starts with the task currently held by the worker. This may bias the training profiles if task rotation varies with age, because lower task rotation implies longer observation periods. The problem is mitigated by the fact that we will take into account seniority as a control variable. Moreover, training profiles appear comparable to those obtained from other sources that specify the observation period; and, when available indirectly from the COI survey, information on the period on which training has occurred does not modify the profile qualitatively (see appendix A for details).

The measures of computerization and organizational innovativeness are built on a rich set of information from the firm level questionnaire (see appendix A). Two synthetic continuous variables are derived from multiple correspondence analyses (see Greenan and Mairesse, 2004, for more details). A highly computerized firm 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. A highly innovative organization jointly uses various new organizational practices like quality certification, just-in-time, total productive maintenance, value analysis, outsourcing, independent profit centres and delegates indirect tasks like quality control or performance improvements to operators. For each firm, the same synthetic variable is created in 1994 and 1997. By difference, we get two continuous variables measuring the intensity of technological and organizational changes between 1994 and 1997. Table 3 displays descriptive statistics on the computerization and organization indexes. The two indexes grow susbtantially between 1994 and 1997. As expected, they are higher in large firms and in industries with high technological intensity.

Finally, we use social security records of the employees' work history (the DADS administrative panel) to build ability indicators (i.e. proxies for a in the theoretical model). The DADS data covers private employment periods, starting

[21] More disaggregated analyses show that access to computer training increases continuously with age for the less educated, consistently with results by Weinberg (2004).

in 1976. We use it to build two measures of individual productive characteristics. A first variable accounts for the number of years of absence from the panel between the first year of observation and the date of the survey (1997). These periods of absence are most likely non-employment period (out of the labor force or unemployed). We build our first proxy as the ratio of this number over the number of years since the worker appeared in the administrative data set. The second variable is a fixed wage effect from a Mincerian wage regression. The estimation is made for the period before the worker enters her current firm. More precisely, the individual effect is estimated in a covariance analysis of log wages controlling for education, sex, experience, industry and time effects. These two variables reflect the success of the worker during her career before entering her current firm; they are therefore interpreted as ability indicators. It must be noted that these two indicators may depend on age by construction: We will therefore allow for interactions with age in the analyses. But, in order to really measure the worker's ability, the indicators must not depend on the type of firm – modern or traditional – in which she is currently employed. This is why the fixed wage effects are estimated before the worker enters her current firm. In turn, building the indicators on spells in preceeding jobs only may introduce biases, if workers in modern firms have longer tenure, for instance. To take an extreme case: if workers in modern firms are not mobile at all (because modern firms have succeeded in reducing turn-over to zero), they will have no previous employer, implying no period of non employment and a missing observation on wage fixed effect. However, such a bias can be controlled for by introducing tenure at current employer as a control variable.

II.B Estimating selection

The theoretical model implies that technical and organizational change may induce earlier or later retirement of older workers from the labor force. One way to test which effect dominates would consist in analyzing workers' departures from modernizing firms.[22] Our model points toward another possibility: test whether older workers still present in modern firms have individual characteristics (proxies for ability a) that show that they have undergone a specific selection process.

More precisely, take one of the ability indicators described above. First, assume that modern and traditional firms recruit from the same pool of workers,

[22] This is the route followed by Aubert et al.(2004).

with the same distribution of ability a, but that, due to technological and organizational change, the optimal threshold for early retirement, a^*, differs in the two types of firms. For instance, early retirement may be more frequent in modern firms (indexed by M) than in traditional firms (indexed by T), i.e. $a^*_M > a^*_T$. Under these conditions, the average productive characteristics of older workers still present in modern firms will be more favorable than those of older workers in traditional firms:

$$\begin{aligned} a^*_M > a^*_T \quad &\Leftrightarrow \quad E(a \mid a \geq a^*_M) > E(a \mid a \geq a^*_T) \\ &\Leftrightarrow \quad E(a \mid Age = 2,\ M) > E(a \mid Age = 2,\ T) \end{aligned}$$

However, it may be that modern firms systematically employ workers with higher ability, regardless of age. In that case, the fact that $E(a \mid Age = 2, M) > E(a \mid Age = 2, T)$ may not be due to earlier retirement of older workers from modern firms. However, the same selectivity should then be observed for younger workers: $E(a \mid Age = 1, M) > E(a \mid Age = 1, T)$. This suggests a difference-in-difference approach to test for specific selection of older workers in modern firms by estimating the sign of Δ:

$$\begin{aligned} \Delta \quad = \quad & [E(a \mid Age = 2,\ M) - E(a \mid Age = 2,\ T)] \\ & - [E(a \mid Age = 1,\ M) - E(a \mid Age = 1,\ T)] \end{aligned}$$

In practice, we do not observe two discrete groups of modern and traditional firms, but rather a continuum, measured by two indexes, the computerization index *Comp* and the organization index *Orga*. We also distinguish four age groups (indexed by $\alpha = 1$ to 4: 20-29, 30-39, 40-49 and 50-59 year old) rather than two. We therefore estimate

(4)

$$\begin{aligned} E(a \mid Age,\ Comp,\ Orga,\ x) = \quad & x\beta + \textstyle\sum_{\alpha=1}^4 g_\alpha \mathbf{1}(Age = \alpha) * Orga \\ & + \textstyle\sum_{\alpha=1}^4 c_\alpha \mathbf{1}(Age = \alpha) * Comp + \sum_{\alpha=1}^4 d_\alpha \mathbf{1}(Age = \alpha) \end{aligned}$$

x is a set of controls that includes industry (based on four levels of technological intensity), firm size (interacted with age), education (interacted with age), sex and tenure of the worker; the dummies $\mathbf{1}(Age = \alpha)$ indicate the age groups. Considering age group 1 as younger workers and age group 4 as older workers, the differences $(g_4 - g_1)$ and $(c_4 - c_1)$ are analogous to Δ. Their interpretation is straightforward: $c_4 - c_1 > 0$ would mean that older workers in more computerized firms have undergone a specific selection process. However, it must be noted that the causal interpretation of that selection is unclear: the selection may be due to technical and organizational change, as in the theoretical model of section 1; but, conversely, it may be that firms with less selected older workers have a lower likeliness of becoming modern.

To summarize, building on proxies for individual ability, we are able to test whether older workers are particularly selected in modern firms. We now show how this is also useful to estimate the *ceteris paribus* impact of technical and organizational change on training profiles.

II.C Measuring the impact of technical and organizational change on training profiles

The statistical model of training incidence for worker i in firm j is:

$$\begin{cases} T_{ij} = & \mathbf{1}[T_{ij}^* > 0] \\ T_{ij}^* = & \sum_{\alpha=1}^{4} k_\alpha \mathbf{1}(Age_i = \alpha) * Orga_j + \sum_{\alpha=1}^{4} m_\alpha \mathbf{1}(Age_i = \alpha) * Comp_j \\ & +x_{ij}\beta + v_i + u_j + \varepsilon_{ij} \end{cases}$$

where T is a binary variable measuring whether the worker has received training or not and T^* is a latent variable; $Orga$ and $Comp$ are the organization and computerization indexes; x is a set of controle variables; $\mathbf{1}(Age = \alpha)$ is a dummy variable for age group α; v_i and u_j are unobserved worker and firm effects; ε_{ij} is an unobserved job effect.

We consider three alternative sets of controls. In model 1, we only control for age groups. In model 2, we control for industry (based on four level of technological intensity), firm size (interacted with age), education (interacted with age), sex and tenure, and for early-retirement frequency within the industry[23] (see appendix tables 2 and 3 for descriptive statistics and the list of categories used in each dimension). Controlling for tenure and for early-retirement frequency raises econometric problems.[24] However, the results are robust to the

[23] The career horizon of workers may indeed impact training decisions. Our purpose is to capture the differences induced by early retirement from the labor force. In 36 industries, we use an exhaustive measure of the size of a cohort of older workers (those who reach the age of 55 to 59 in 2000) at two dates: 1995 and 2000. We then compute the growth rate of that cohort in each industry (in most cases, this growth rate is of course negative, due to early withdrawals from the workforce). This measure of career horizon has a major drawback: as it is done at the industry level, it cannot be disentangled from other unobserved sources of heterogeneity across industries.

[24] Due to endogenous mobility, estimates of tenure effects are likely to be biased (though the direction of the bias is unclear) and this may contaminate the estimated age effects.

As for early-retirement practices, they may be spuriously correlated with training pracchoice of including or not these controls: we decide to keep them to make clear that coefficients k_α and m_α really measure the effects of technical and organizational change across ages rather than those of other correlated dimensions such as tenure.

However, as implied by the theoretical model, individual effects v_i that include the worker ability may be correlated with training, age and the computerization and organization indexes, if there has been specific selection of older workers in modern firms. This would bias the estimation of coefficients k_α and m_α. Model 3 addresses this selection bias issue by adding the selection indicators, interacted with age, to the control variables.[25] If the indicators are satisfactory measures of ability a, this amounts to estimating the impact of the computerization and organization indexes conditional on a (rows 1 to 3, table 1), thus making sure that the estimates only capture the indirect effect.

The endogeneity of technical and organizational change implies that unobserved firm effects u_j may also be correlated with the organization and computerization indexes, biasing the estimation.[26] For instance, younger managers could introduce technological and organizational change and discriminate against training their older workers. This would bias our results toward a negative relative effect of computerization and organizational change on the access of older workers to training. Such permanent unobserved heterogeneity is usually dealt with by estimating equations in (long) differenced form (see for instance Caroli and Van Reenen, 2001). [27] We do not observe access to training during successive periods and are not able to estimate the equation in long difference. Another solution is to rely on a source of variation that drives computerization and organizational change and that is independent from training. The COI survey was designed to produce such instruments. The employer was asked about seven

tices. We checked that this was not driving the results by instrumenting the early-retirement practices by the overall evolution of the size of each industry.

[25] As the ability indicators are based on the work history of the workers in previous jobs, there are missing observations. For these observations, we impute the median value in the age group. We then add a third binary indicator (interacted with age) that takes value 1 if one of the two initial ability indicators was missing, and 0 otherwise. This approach allows to keep the complete sample in regressions. It does not yield significantly different results from the approach that uses only the subsample without missing ability indicators.

[26] On the stringent conditions to obtain consistent estimates of complementarities – here, between training and computerization or organizational design – see Athey and Stern (1998).

[27] Bresnahan et al. (2002) argue that training is already in differenced form (as it is a variation in the stock of human capital), thus removing permanent unobserved heterogeneity. In our case, however, it is clear from the above example that unobserved heterogeneity of the management may affect both the skill level and the skill evolution (the training) of the workforce.

"constraints" that had influenced her organizational (respectively technological) decisions between 1994 and 1997. Five of these constraints – administrative rules, constraints imposed by clients, by suppliers, by increased competition and by market uncertainty – can be viewed as exogenous sources of variations that drive organizational and technological decisions,[28] arguably without impacting training choices. In practice, a problem with this set of instruments is that they jointly explain a small part of the variables of interest (around 5% of variance). We are thus led to complement these instruments using the (short) panel dimension of the COI survey. We instrument the *level* of the computerization index (respectively of the organization index) with the technical (respectively organizational) *change* between 1994 and 1997. This instrumentation solves the permanent unobserved heterogeneity problem in the sense that it removes permanent firm effects from the source of identification.

The second problem is simultaneity. For example, an unfavorable demand shock can induce the firm to change both its training policy and to reorganize itself in order to reduce costs. The usual solution to that problem relies on lagged instruments. However, the shortness of our panel[29] does not enable us to control both for permanent unobserved heterogeneity and for short-run simultaneity. We are therefore unable to control for this possible simultaneity bias. Its direction is unclear: if reorganization is aimed at reducing costs, it could be accompanied by less training; on the other hand, if reorganizing is an investment made possible by higher profits, it could be correlated with a rise in training expenditures. Moreover, we are concerned with differences in the bias that could occur across ages. These differences are hard to predict; it does not seem that they should be large nor systematic.

Overall, this identifying strategy, although it does not solve all potential problems, has the advantage of being partially testable. Indeed, we are left with twelve instruments for two potentially endogenous variables. A test of overidentifying restrictions is therefore possible (see appendix B). The exogeneity of the instruments is rejected for computer training[30] but it is clearly not rejected for

[28] One caveat applies: these are declared constraints. The subjective perception of the constraints may reintroduce endogeneity (e.g., declaring that decisions were constrained by administrative rule may denote that some changes were desired by the firms for some endogenous reasons, making the management aware of constraints).

[29] Remember that the characteristics of the firms are observed only twice (in 1994 and 1997) and that access to training is observed only once.

[30] One may think that this is due to the declared constraints on technology adoption that are used as instruments, as they may be correlated with computer training decisions. However, the overidentifying restrictions are still rejected if we remove these five instruments. Given the limitations of the statistical test (which may over-reject) and the satisfactory results for the

training in the main task, in management and in teamwork, which gives some confidence in the instruments chosen.

The dependent variable is a binary one: access to training. In model 1 to 3, we use a probit specification, correcting standard errors for clustering in firms (robust estimates). For model 4, the instrumentation with two-stage least squares is inappropriate. We use a two-step estimation method developed by Smith and Blundell (1986) and Rivers and Vuong (1988). In a first stage, potentially endogenous variables are regressed on the instruments and the controls by OLS. In a second stage, we estimate a probit model, augmented by the estimated residuals from the first stage. Average partial effects are then computed at sample mean. Standard errors are estimated by bootstrap.

Formally, the first stage writes:

$$Orga_j = x'_{ij}\beta_1 + z'_j\gamma_1 + v_{1ij}$$
$$Comp_j = x'_{ij}\beta_2 + z'_j\gamma_2 + v_{2ij}$$

where x is the same vector of controls as in model 3, z the vector of instruments (five constraints on computerization, five constraints on organization, and changes in computerization and in organization), and v_1 and v_2 are the residuals. In the second stage, we estimate the following probit (model 4):

$$P(T_{ij} = 1) = \Phi[\alpha_1 Orga_j + \alpha_2 Comp_j + x'_{ij}\beta + \xi_1\widehat{v_{1ij}} + \xi_2\widehat{v_{2ij}}]$$

where $\widehat{v_{1ij}}$ and $\widehat{v_{2ij}}$ are the residuals estimated from the first step. The exogeneity of the organization and computerization indexes can be checked by testing the nullity of the coefficients ξ_1 and ξ_2 (Smith and Blundell, 1986). This two-step estimation procedure is repeated separately for each age group.

III. RESULTS

III.A Selection

Table 4 presents the selection effects of technological and organizational change. Panel A and B display the results of the same regressions in different ways. Panel

other three types of training, we maintain our initial choice of instruments.

A displays estimates for g_α and c_α in equation 4, to see whether workers of age group α have higher ability indicators in modern firms than in traditional firms. A positive g_α (or c_α) indicates higher ability in the case of the wage fixed effect indicator, and lower ability in the case of the non employment indicator. Panel B displays differences across age groups; these estimates can be computed directly from panel A by difference (e.g. $g_2 - g_1$) but panel B also provides standard errors to assess whether differences are significant.

Looking at wage fixed effects first (first column of panels A and B), it appears that firms with a higher organization index tend to employ 'high wage workers' (workers who earned high wages in their previous jobs) more often: the coefficients g_α are positive for each age group, although statistically significant only for the 30-39 age group. Point estimates are sizeable: an increase of the organization index by one standard deviation implies an increase in previous wages by 1 to 10 percent. Differences across age groups are not statistically significant (panel B): if anything, older workers would be *less* selected than younger workers in firms with higher organization index ('difference-in-difference' estimates of 5 percent), but the difference is not significant. By contrast, more computerized firms do not appear to be generally more or less selective than less computerized firms: differences in previous wages range from -3 percent to $+11$ percent, depending on the age group. However, a clear age pattern emerges; older workers in more computerized firms are specifically high wage workers, as shown in panel B. The 'difference-in-difference' between older and younger workers is 14 percent, significant at a 10% level of confidence. To summarize, using wage fixed effects as an ability indicator mainly shows that older workers in more computerized firms are specifically selected; this is not true for older workers in firms with a higher organization index.

These findings are broadly confirmed by the second ability indicator, based on the share of time spent non employed. In firms with a higher organization index, the 20-29 age group is the only one to have significatively more favorable characteristics (a 1.75 percentage point lower share of time spent non employed, see panel A, second column). Workers aged 30 to 59 appear to be less selected, by comparison (panel B). However, this cannot be attributed to less frequent early departure of older workers, as no significant differences appear between 30 and 59. By contrast, there is evidence of a specific selection of older workers in more computerized firms. Workers aged 40 and above tend to have spent less time non employed and the 'difference-in-difference' is statistically significative.

These results show a specific selection of older workers in more computerized firms, though not in firms with a higher organization index. However, the causal interpretation is not clear cut. This differentiated selection could result from two main mechanisms: either modern firms and older workers separate more frequently or firms with a higher share of less productive older workers are less likely to adopt innovations. In other words, the evidence is consistent with the results by Aubert et al. (2004) showing a decrease in the employment of older workers in modern firms. But it is also consistent with the result by Diaye et al. (2004) according to which manufacturing firms with a majority of older workers are less likely to adopt advanced uses of information technology.

III.B Impact of the organization index on training profiles

Table 5 displays the results of models 1, 2, 3 and 4 concerning the impact of the organization index on training incidence.[31] The coefficients estimate the effect of a one standard deviation increase in the organization index on the probability to receive training.[32] Table 5 focuses on training in the worker's main task. Results for other types of training will be displayed graphically.[33]

Consider all age groups together first. The raw correlation between the organization index and access to training (model 1) is positive. Controlling for composition effects reduces the estimates by about one fourth (model 2). Controlling for selection (model 3) and for selection and potential endogeneity (model 4) reduces the estimates by another third. Selection effects go in the expected direction: the impact on training is reduced once taken into account the higher ability of workers in modern firms. However, they are not very large.[34] The exogeneity of the organization index is not rejected at the usual confidence level (the t-statistic is 1.8). Estimates from model 3 are therefore the preferred ones. On average, a more innovative organization increases the probability to receive training by 5.7 percentage points (statistically highly significant); the increase is higher for younger workers aged 20 to 29, but no significant difference appears between the ages of 30 to 59. Overall, training increases at all ages, and there is no evidence of a relative decrease for older workers.

[31] Although the impact of the computerization index has been estimated simultaneously, results are presented separately for the sake of clarity.

[32] The two-period theoretical model considered the intensity of training at each period rather than training incidence. However, the incidence of training on shorter periods can be interpreted as a measure of training intensity on longer periods like periods 1 and 2 in the model.

[33] Tables similar to table 3 for training in computer, management and teamwork are available upon request.

[34] This may indicate that selection bias is not important, or that we have not been able to control for it completely.

Figure 3 enables an easier reading of the results for the four different types of training. It shows the average training profile and the estimated impact of a one standard deviation increase in the organization index (the dashed lines show 95% confidence intervals around this estimate). Estimates are computed from model 3 as the exogeneity of the organization index is not statistically rejected for any of the training types.[35]

The top graph on the left repeats the results of table 5: access to training increases at all ages in firms with a modern organization, although the difference is at the limit of significativity for older workers. The incidence of training in computer and in management is not affected by the organization index. It is possible that the different effects of organizational change on these two types of training cancel out. But it seems more likely that each of these effects is low: concerning computers and management, it seems plausible that the rhythm of skills depreciation, the obsolescence of schooling and the return to training are not affected by the type of organization.

Conversely, the incidence of training in teamwork significatively increases at all ages in firms with a more innovative organization. The use of new organizational practices tends to increase interdependencies between workers in information and in the work done. Teamwork could be viewed as a mean to deal with these interdependencies by internalizing them within a group of strongly interconnected persons. Interestingly, the fact that younger and older workers are more frequently trained to teamwork indicates that mature employees may acquire the interaction skills as well as younger workers.

Figure 5 displays results from the same estimations, stratified by occupation. We distinguish manual workers and unskilled workers, on the one hand,[36] and managers and technicians, on the other hand.[37] The increase in training to main task due to a higher organization index occurs at all ages in both group; the fact that it is smaller for managers and technicians may be due to the fact that training incidence rates are approaching one. Two other features are noticeable: there are signs that a higher organization index leads to a rise in the computer training of older manual workers. This may be interpreted

[35] Model 4 yields qualitatively similar but less precisely estimated results.

[36] We group unskilled white collars with manual workers, but they are only a minority in this sample from the manufacturing sector.

[37] With smaller categories, occupation is endogenous and correlated with age, as experience accumulation induces upward mobility. This is why education (a predetermined variable) has been preferred as a control variable. However, there is little mobility between the two broad occupation groups we distinguish now, so that they are useful to check the robustness of the results as well as to refine them.

according to Weinberg's (2004) idea that experience facilitates learning for less skilled workers. Second, a higher organization index increases the probability that older managers and technicians receive training in management. Overall, this disaggregated analysis confirms and refines the aggregate results.

III.C Impact of the computerization index on training profiles

Table 6 follows the same logic as table 5. Results are then summarized in figure 4 that compares average access to training and access to training in a highly computerized firm.[38]

The impact of technology on training in the main task, management and teamwork is not significant, regardless of age. This contrasts with the impact of the organization index. Although computerization and organizational change are correlated, they appear to have different effects on training outcomes.

Not surprisingly, computerization has a strong impact on the incidence of computer training. However, this positive impact disappears for workers older than 50. One explanation may be the shorter payback period. However, this argument does not seem to hold for training in the main task or in teamwork (figure 3); it is unclear why it should be valid for training in computer. A more promising explanation may be schooling obsolescence and a generation effect that would explain that older workers are less prone to acquire computer skills.

Figure 6 displays results by broad occupation groups. The negative impact of firms' computerization on the probability to receive computer training holds only for manual workers and unskilled white collars. This contrasts with the favorable impact of the *organization* index on the frequency of computer training for older manual workers. A tentative explanation for this contrast would be that the computer skills that need to be learned are quite involved in the case of a computerized firm, so that skill obsolescence and learning difficulties disadvantage older manual workers, whereas computer skills needed in a modern organization are simpler, and older manual workers can build on their experience to acquire them. By contrast, computer training increases at all ages for managers and technicians in more computerized firms: the obsolescence effect does not seem to play.

[38] The estimates are also taken from model 3 (the exogeneity of computerization is not statistically rejected).

IV. CONCLUSION

The results lead to reject the hypothesis that the relative access of older workers to training systematically decreases as a result of computerization and organizational change. In modern firms, access to various types of training is unchanged or higher for all age groups, without relative disadvantage for older workers. The impact of computerization on the incidence of computer training is a noticeable exception: Among manual workers and unskilled white collars, the rise in training benefits only those below 50. Nonetheless, a significant share of workers aged 50 and above still receives computer training; overall, this result 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 Well, 2002).

The fact that the effects of computerization and organizational change differ across types of training is consistent with the general theoretical indetermination. The magnitude of the effects of accelerated skill depreciation, schooling obsolescence and increased return to training may indeed be different for the various types of training. It appears that the unfavorable obsolescence effect dominates only for computer training incidence among manual workers.

We also find evidence of a stronger selection of older workers in more computerized firms. This selection appears in more favorable average individuals characteristics for older workers still employed in modern firms. Overall, we conclude that computerization has an adverse impact on the employment prospects of older workers, through a direct effect on productivity rather than through insufficient access to training.

How far do we go in explaining the evolution of training profiles observed on figure 1? Relative access to training in modern firms is not systematically lower for older workers, as could be expected from the 1993 more sharply declining profile. However, this declining profile may be the result of a composition effect, as older workers appear to be selected away from modern firms, which train their workers more. Our results can thus qualitatively explain the aggregate change in the training profiles, in a somewhat subtle way. To assess quantitatively how much is explained, one would need to quantify the selection better – an area for further research. This seems a promising venue, though our 1994-1997 observations will never be matched perfectly with changes that occurred between 1985 and 1993.

The question that comes next is whether training will be sufficient in the longer run to compensate the unfavourable direct effect on older workers' productivity. Panel data would help solve this issue as it allows to distinguish between short and long run effects. Panel data would also be needed to complete the econometric analysis of difficult endogeneity issues. As for the SBTC literature, a key step is to understand the conditions of the adoption of computerization and organizational change better.

APPENDIX

A. Data appendix

The main data source is the COI survey (Changement organisationnel et informatisation, 1997), a French matched employer-employee survey which was designed to produce accurate information on computerization and organizational change at the firm and at the job level. 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 business section of the survey in manufacturing while the Ministry of agriculture (SCEES) took care of food industries.

The questions that we used to measure computerization and organizational change are displayed in figures 7 and 8. The question numbers are those of the questionnaire: our presentation does not follow the order of the questionnaire. Descriptive statistics on the computerization and organizational index we build from these questions are shown in table 3. 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. Thanks to this file, small samples of two or three employees with at least one year of seniority have been randomly sampled within each firm, leading to a sample of 6 796 employees. While selecting workers, information about their past trajectory registered in the DADS panel has been kept. This historical file has been used to compute ability indicators.

The labour force section of the survey has been conducted by the Ministry of Labor (DARES). Employees have been interviewed by phone, in the context of their homes, or face to face when they could not be reached by phone. The design of the survey device (method and questionnaires) along with the coordination of the survey implementation has been conducted by the Centre d'Etudes de l'Emploi (under the direction of Nathalie Greenan). 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 guaranty the quality of the information.

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)

Q27bis a. Since when have you had employees under your authority?

Q27bis c. In addition to your initial training, did you receive specific training to this role in management? (Yes/No)

Q40bis d. Did you receive specific training to teamwork? (Yes/No)

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)

Q61bis. Did this training session last...? (less than three full days/ more than three full days)

This leads to 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. The observation period, as defined in the survey guidelines, starts with the task currently held by the worker. Depending on the rhythm of task rotation, this period may thus differ for workers of different ages in different types of firms. However, we can use question Q60 on the period for which computers have been used to get a proxy of this period of observation. We checked that the shape of training profiles (according to age) is not substantially modified by considering separately those who have been using computers for more and less than five years. We checked the same for training to management using question Q27bis a. This shows that the training profiles we estimate are not artefacts of differences in the length of the observation periods at different ages. Another check is to compare our training profiles to those obtained from other sources that specify the observation period (the FQP survey, the Formation continue 2000 survey). They turn out to be similar once we pool together the five types of training from the COI survey (these five types of training are not distinguished in other sources).

Last, figure 1 uses the Formation et qualification professionnelle (FQP), a worker survey that took place in 1977, 1985 and 1993, with questions covering employment and training experience over the whole career and with a focus on the previous five years. In particular, the incidence of training financed by the employer over the previous five years can be measured consistently across the three surveys (see Behaghel [2002] for more details).

B. Test of overidentifying restrictions

The model to estimate is:

(5) $T = 1[\alpha_1 Orga + \alpha_2 Comp + x'\beta + u > 0]$,

(6) $Orga = x'\beta_1 + z'\gamma_1 + v_1$,

(7) $Comp = x'\beta_2 + z'\gamma_2 + v_2$.

where

$$(8) \quad \begin{pmatrix} u \\ v_1 \\ v_2 \end{pmatrix} \sim \mathrm{N}\left(0, \begin{pmatrix} 1 & \eta_1 & \eta_2 \\ \eta_1 & \tau_1^2 & \eta_{12} \\ \eta_2 & \eta_{12} & \tau_2^2 \end{pmatrix}\right).$$

u is correlated with $Orga$ and $Comp$ through v_1 and v_2 so that a simple probit estimation of (5) generally yields inconsistent estimates of α_1 and α_2. Following Smith and Blundell (1986) and Rivers and Vuong (1988), we augment equation (5) to take into account v_1 and v_2. Let us write

$$u = \theta_1 v_1 + \theta_2 v_2 + e,$$

with e independent of v_1 and v_2. Given the stochastic assumptions from (8),e is normally distributed with standard error σ_e and mean 0, and independent of $Orga$, $Comp$, x, z, v_1 and v_2. Hence, rewriting $\alpha_{e1} = \frac{\alpha_1}{\sigma_e}$, $\alpha_{e2} = \frac{\alpha_2}{\sigma_e}$, etc.:

$$(9) \quad E\left(T \mid Orga, Comp, x, v_1, v_2\right) = \Phi\left(\alpha_{e1} Orga + \alpha_{e2} Comp + x'\beta_e + \theta_{e1} v_1 + \theta_{e2} v_2\right).$$

As v_1 and v_2 are unobserved, Smith and Blundell (1986) and Rivers and Vuong (1988) propose to replace them by the estimated residuals from the OLS estimation of equations (6) and (7), and to estimate a probit model. This is the estimation procedure used in the text. However, to test overidenfying restrictions, we now rather look for moment conditions implied by the model. Replacing v_1 and v_2 in (9) by their true expressions from equations (6) and (7), we have:[39]

$$(10) \quad E\left(T - \Phi\begin{pmatrix} \alpha_{e1} Orga + \alpha_{e2} Comp + x'\beta_e \\ +\theta_{e1}(Orga - x'\beta_1 - z'\gamma_1) \\ +\theta_{e2}(Orga - x'\beta_2 - z'\gamma_2) \end{pmatrix} \mid Orga, Comp, x, z\right) = 0.$$

Writing $u_g \equiv T - \Phi\left(\alpha_{e1} Orga + \alpha_{e2} Comp + x'\beta_e + \theta_{e1}(Orga - x'\beta_1 - z'\gamma_1) + \theta_{e2}(Orga - x'\beta_2 - z'\gamma_2)\right)$, we get a first series of $Y + I + E$ moment conditions (where Y is the number of po-

[39] Note that v_1 and v_2 are linear combinations of $Orga$, $Comp$, x and z so that they are redundant in conditioning.

tentially endogenous variables (here, $Y = 2$), I is the number of exogenous variables x included in the training equation and E is the number of exogenous variables z excluded from the training equation):

(11) $E(u_g \cdot t) = 0$ with $t = (Orga\ Comp\ x'\ z')'$.

Equations (6), (7) yield $Y(I + E)$ moment conditions:

$$\begin{array}{llcl} (12) & E(v_1 \cdot s) & = & 0 \text{ with } s = (x'\ z')', \\ (13) & E(v_2 \cdot s) & = & 0. \end{array}$$

The row vector of parameters to estimate can be written $\theta' = (\alpha_{e1}\ \alpha_{e2}\ \beta_e'\ \theta_{e1}\ \theta_{e2}\ \beta_1'\ \gamma_1'\ \beta_2'\ \gamma_2')$. We stack equations (11), (12) and (13) together to rewrite the moment conditions as

$$E(g(\theta)) = 0,$$

where g: $\Re^{2Y+I+Y(I+E)} \rightarrow \Re^{Y+I+E+Y(I+E)}$ and $\theta \in \Re^{2Y+I+Y(I+E)}$.

The model is overidentified if the number of independent moment conditions exceeds the dimension of θ or, equivalently, if the number of exogenous variables excluded from the training equation exceeds the number of potentially endogenous variables, i.e. if $E > Y$. In that case, it is possible to test the internal consistency of the statistical model by a test of overidentifying restrictions. The null hypothesis to be tested is that there exists a parameter θ such that $E(g(\theta)) = 0$. The test statistic is $S = ng(\widehat{\theta}_n)'\Omega_n^{-\frac{1}{2}} R_n \Omega_n^{-\frac{1}{2}} g(\widehat{\theta}_n)$ where $\widehat{\theta}_n$ is any consistent estimator of θ and

$$\begin{array}{l} \Omega_n \xrightarrow{p} \Omega = E(g(\theta)g(\theta)'), \\ G_n \xrightarrow{p} G = E\left(\frac{\partial g(\theta)}{\partial \theta'}\right), \\ R_n = I - \Omega_n^{-\frac{1}{2}} G(G\Omega^{-1}G)^{-1} G\Omega_n^{-\frac{1}{2}}. \end{array}$$

Under the null, S is asymptotically distributed as chi-square with $E - Y$ degrees of freedom (McFadden and Newey, 1994, pp. 2231-32). To compute S, we use $\widehat{\theta}_n$ from the consistent two-stage estimation procedure proposed by Smith and Blundell (1986) and Rivers and Vuong (1988) (see above).

The values taken by S for the four types of training are the following:

Task	Computer	Management	Teamwork
5.44	29.61	8.45	7.56

A test with 5% level rejects the null whenever the observed statistics is larger than 18.31 (chi-square with 10 degrees of freedom). Hence, the test does not reject the validity of the instruments to estimate the equations for training in the main task, in management and teamwork, but it rejects it to estimate the computer training equation.

		Direct effect	Indirect effect (through training)		
		Decreased productivity (y_2 falls)	Accelerated productive skills' depreciation (λ_1 falls)	Schooling obsolescence (λ_e falls)	Increased return on productive skills (r falls)
Two-period jobs	Training T_1^*	=	-	=	+
	Training T_2^*	=	=	-	+
One-period jobs	Training T_1	=	=	=	+
Share of workers retiring early $G(a^*)$		+	+	+	-
Average training	Among younger workers	-	-	-	+
	Among older workers	+	+	-/+	-/+

TAB. 1: Predicted impact of technical and organizational change on training and employment

		Share in the sample	Incidence of training in the main task	Incidence of computer training	Incidence of training in management	Incidence of training in teamwork
Complete sample		100%	54%	31%	10%	12%
By age	20-29	17%	54%	26%	3%	8%
	30-39	33%	56%	31%	8%	10%
	40-49	33%	55%	32%	13%	14%
	50-59	17%	50%	30%	16%	17%
By tenure	1-4 years	18%	53%	27%	6%	9%
	5-9 years	25%	53%	31%	9%	10%
	10-14 years	13%	55%	32%	9%	10%
	15-19 years	13%	56%	32%	11%	14%
	>20 years	31%	55%	32%	14%	15%
By firm size	50-199	40%	43%	21%	6%	7%
	200-1999	44%	58%	33%	11%	13%
	>1000	16%	72%	48%	17%	22%
By industry's technological intensity	High	9%	70%	49%	10%	18%
	Medium-high	19%	64%	40%	13%	15%
	Medium-low	30%	53%	28%	8%	11%
	Low	42%	47%	25%	10%	11%
By education	College	31%	70%	52%	17%	21%
	High school diploma	42%	53%	27%	9%	9%
	<High school	27%	38%	13%	5%	7%

Sample size: 4394 observations

TAB. 2: Training incidence (descriptive statistics)

		Share in the sample	Mean of firm's organization index in 1997	Mean of firm's computerization index in 1997	Mean of firm's organization index in 1994	Mean of firm's computerization index in 1994
Complete sample		100%	0	0	-0,79	-0,90
standard deviation		-	*1*	*1*	*0,71*	*0,83*
By age	20-29	17%	-0,05	-0,06	-0,84	-0,97
	30-39	33%	-0,02	-0,04	-0,79	-0,92
	40-49	33%	-0,01	0,01	-0,79	-0,89
	50-59	17%	0,10	0,11	-0,72	-0,84
By tenure	1-4 years	18%	-0,07	-0,04	-0,84	-0,96
	5-9 years	25%	-0,02	-0,08	-0,82	-0,97
	10-14 years	13%	-0,09	-0,08	-0,82	-0,97
	15-19 years	13%	0,00	0,02	-0,79	-0,88
	>20 years	31%	0,09	0,11	-0,72	-0,80
By firm size	50-199	40%	-0,62	-0,70	-1,10	-1,37
	200-1999	44%	0,27	0,27	-0,64	-0,76
	>1000	16%	0,86	1,03	-0,40	-0,11
By industry's technological intensity	High	9%	0,33	0,56	-0,58	-0,59
	Medium-high	19%	0,36	0,29	-0,63	-0,70
	Medium-low	30%	0,12	0,00	-0,74	-0,91
	Low	42%	-0,31	-0,24	-0,93	-1,06
By education	College	31%	0,14	0,20	-0,71	-0,78
	High school diploma	42%	-0,03	-0,04	-0,81	-0,93
	<High school	27%	-0,11	-0,16	-0,84	-1,00

Sample size: 4394 observations.

TAB. 3: Organization and computerization indexes (descriptive statistics)

			A. Impact for each age group			B. Differences in impact between age groups	
			Dependent variable			Dependent variable	
			Individual wage fixed effect (at previous employers)	Share of years non employed (%)		Individual wage fixed effect (at previous employers)	Share of years non employed (%)
Impact of a one standard deviation increase in the organization index	20-29 year old	g_1	0,06	-1,75		ref	ref
			0,05	0,70		-	-
	30-39 year old	g_2	0,10	0,14	g_2-g_1	0,03	1,88
			0,03	0,49		0,06	0,85
	40-49 year old	g_3	0,03	-0,26	g_3-g_1	-0,03	1,49
			0,04	0,49		0,06	0,86
	50-59 year old	g_4	0,01	0,16	g_4-g_1	-0,05	1,91
			0,06	0,72		0,07	1,01
Impact of a one standard deviation increase in the computerization index	20-29 year old	c_1	-0,03	1,64		ref	ref
			0,06	0,77		-	-
	30-39 year old	c_2	-0,01	0,22	c_2-c_1	0,03	-1,41
			0,04	0,52		0,07	0,93
	40-49 year old	c_3	0,04	-0,35	c_3-c_1	0,07	-1,99
			0,04	0,53		0,07	0,93
	50-59 year old	c_4	0,11	-0,71	c_4-c_1	0,14	-2,35
			0,06	0,81		0,08	1,12
Number of observations			3 326	4 042		3 326	4 042

OLS regressions of the dependent variables (ability indicators) on the organization and computerization indexes interacted with age groups.
Standard error in small characters below each coefficient (see equation 4 in the text for coefficients' definitions).
Control variables: age group; education (interacted with age); sex; tenure; firm size (interacted with age); industry's technological intensity.

TAB. 4: Selection: ability indicators according to firm's organization and computerization indexes

		Dependent variable: Incidence of training in the main task (binary variable)			
		(1)	(2)	(3)	(4)
Firm's organization index	All age groups	0,077	0,058	0,057	0,035
		0,010	0,011	0,011	0,019
	20-29 year old	0,111	0,090	0,091	0,022
		0,024	0,026	0,026	0,042
	30-39 year old	0,077	0,055	0,055	0,067
		0,017	0,018	0,018	0,032
	40-49 year old	0,075	0,051	0,048	0,022
		0,017	0,019	0,019	0,031
	50-59 year old	0,051	0,045	0,042	0,016
		0,025	0,027	0,028	0,050
Control of composition effects		No	Yes	Yes	Yes
Ability indicators		No	No	Yes	Yes
Instrumented		No	No	No	Yes
Exogeneity test (tstat - coef. on residuals from stage 1)	All age groups				1,800
	20-29 year old				0,525
	30-39 year old				1,280
	40-49 year old				0,707
	50-59 year old				0,525
Share of variance explained by instruments	All age groups				53%
	20-29 year old				54%
	30-39 year old				51%
	40-49 year old				55%
	50-59 year old				51%
Number of observations	All age groups	4 393	4 393	4 393	4 393
	20-29 year old	-	-	-	730
	30-39 year old	-	-	-	1 461
	40-49 year old	-	-	-	1 476
	50-59 year old	-	-	-	726

The coefficients display the impact of the firm's index on the probabilty to receive training, by age group
(average partial effects, evaluated at sample mean).
Standard errors (corrected for clustering in firms and, in the case of model 4, estimated by boostrap) are below the coefficients
in small characters.
Models 1 to 3: probit model; model 4: two-stage estimation, done separately for each age group (see text).
Control variables model 1: age group.
Control variables model 2: age group, education (interacted with age); sex; tenure; firm size (interacted with age);
industry's technological intensity; industry's frequency of early retirement
Control variables models 3 and 4: same as model 2; ability indicators (interacted with age).

TAB. 5: Impact of the firm's organization index on the incidence of training in the main task

		Dependent variable			
		Incidence of training in the main task (binary variable)			
		(1)	(2)	(3)	(4)
Firm's technology index	All age groups	0,066	0,021	0,020	0,018
		0,010	0,012	0,012	0,021
	20-29 year old	0,048	0,009	0,009	0,053
		0,024	0,027	0,027	0,052
	30-39 year old	0,065	0,025	0,023	0,003
		0,017	0,019	0,019	0,038
	40-49 year old	0,065	0,015	0,015	-0,006
		0,017	0,020	0,020	0,040
	50-59 year old	0,100	0,041	0,041	0,051
		0,026	0,030	0,031	0,055
Control of composition effects		No	Yes	Yes	Yes
Ability indicators		No	No	Yes	Yes
Instrumented		No	No	No	Yes
Exogeneity test (tstat - coef. on residuals from stage 1)	All age groups				0,953
	20-29 year old				0,656
	30-39 year old				0,758
	40-49 year old				0,247
	50-59 year old				0,426
Share of variance explained by instruments	All age groups				43%
	20-29 year old				43%
	30-39 year old				42%
	40-49 year old				44%
	50-59 year old				44%
Number of observations	All age groups	4 393	4 393	4 393	4 393
	20-29 year old	-	-	-	730
	30-39 year old	-	-	-	1 461
	40-49 year old	-	-	-	1 476
	50-59 year old	-	-	-	726

The coefficients display the impact of the firm's index on the probabilty to receive training, by age group
(average partial effects, evaluated at sample mean).
Standard errors (corrected for clustering in firms and, in the case of model 4, estimated by boostrap) are below the coefficients
in small characters.
Models 1 to 3: probit model; model 4: two-stage estimation, done separately for each age group (see text).
Control variables model 1: age group.
Control variables model 2: age group, education (interacted with age); sex; tenure; firm size (interacted with age);
industry's technological intensity; industry's frequency of early retirement
Control variables models 3 and 4: same as model 2; ability indicators (interacted with age).

TAB. 6: Impact of computerization on the incidence of training in the main task

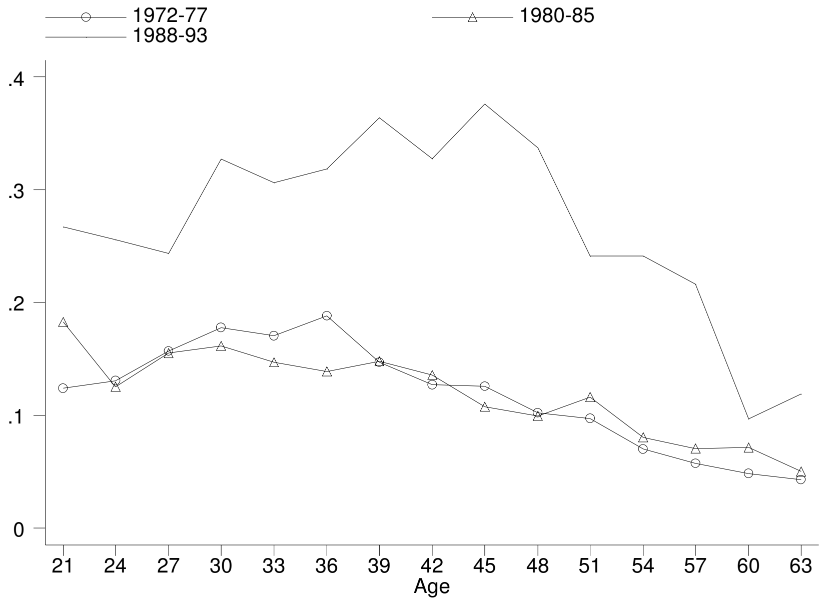

Figure 1: Training incidence according to age and to the period (FQP survey)

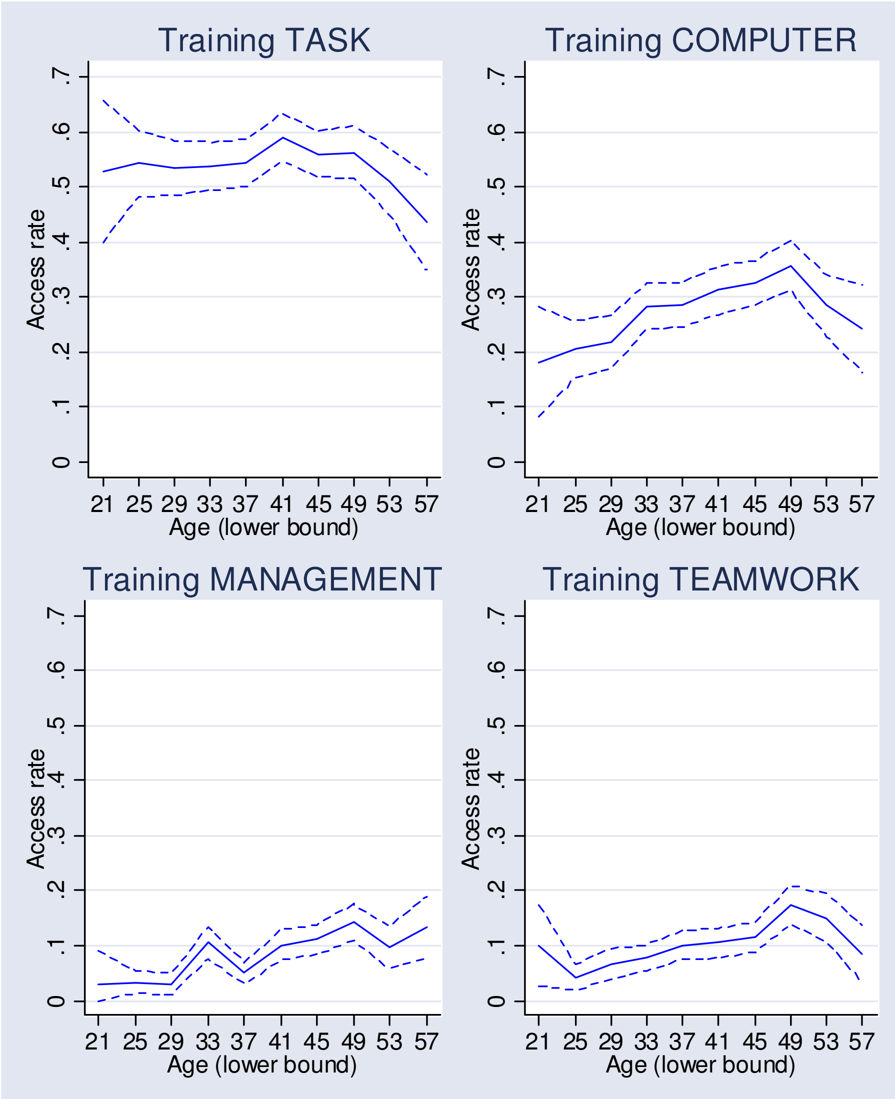

Figure 2: Incidence of different types of training according to age

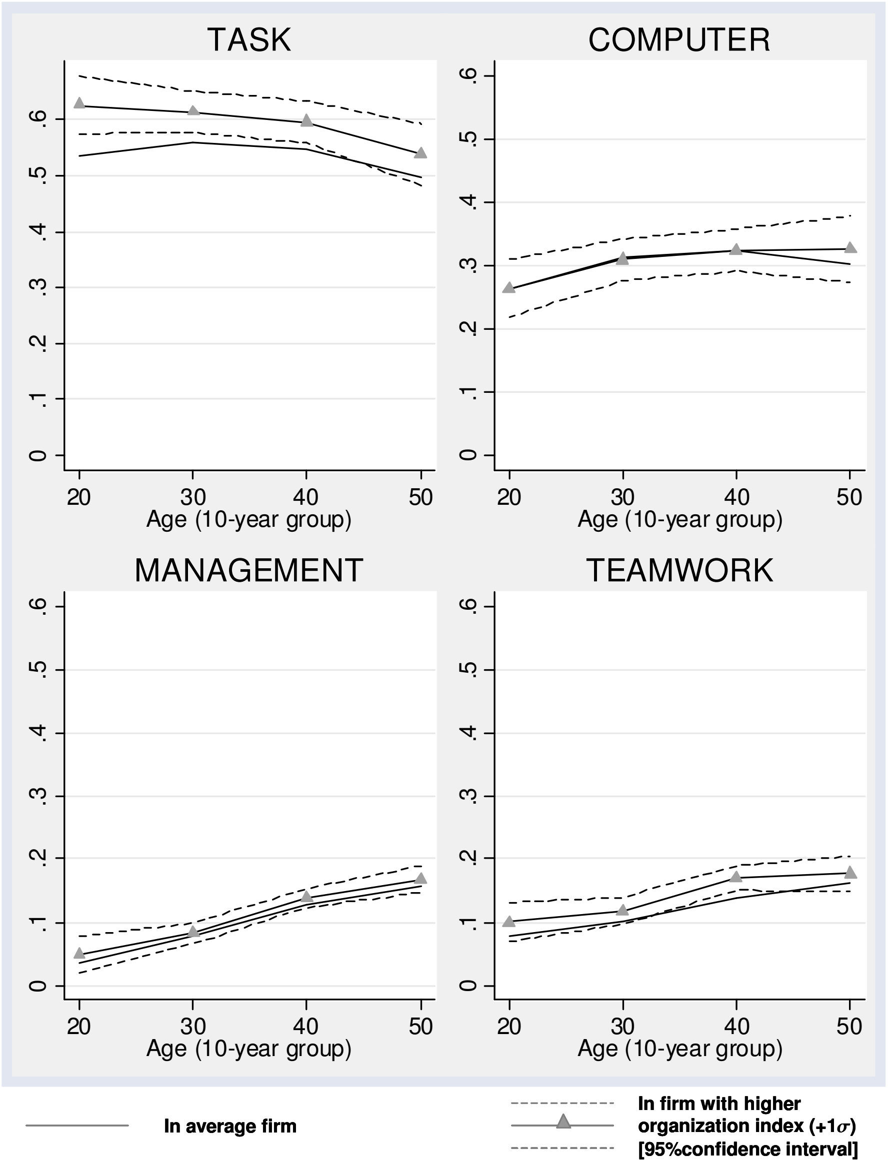

Figure 3: Impact of the organization index on the incidence of four types of training

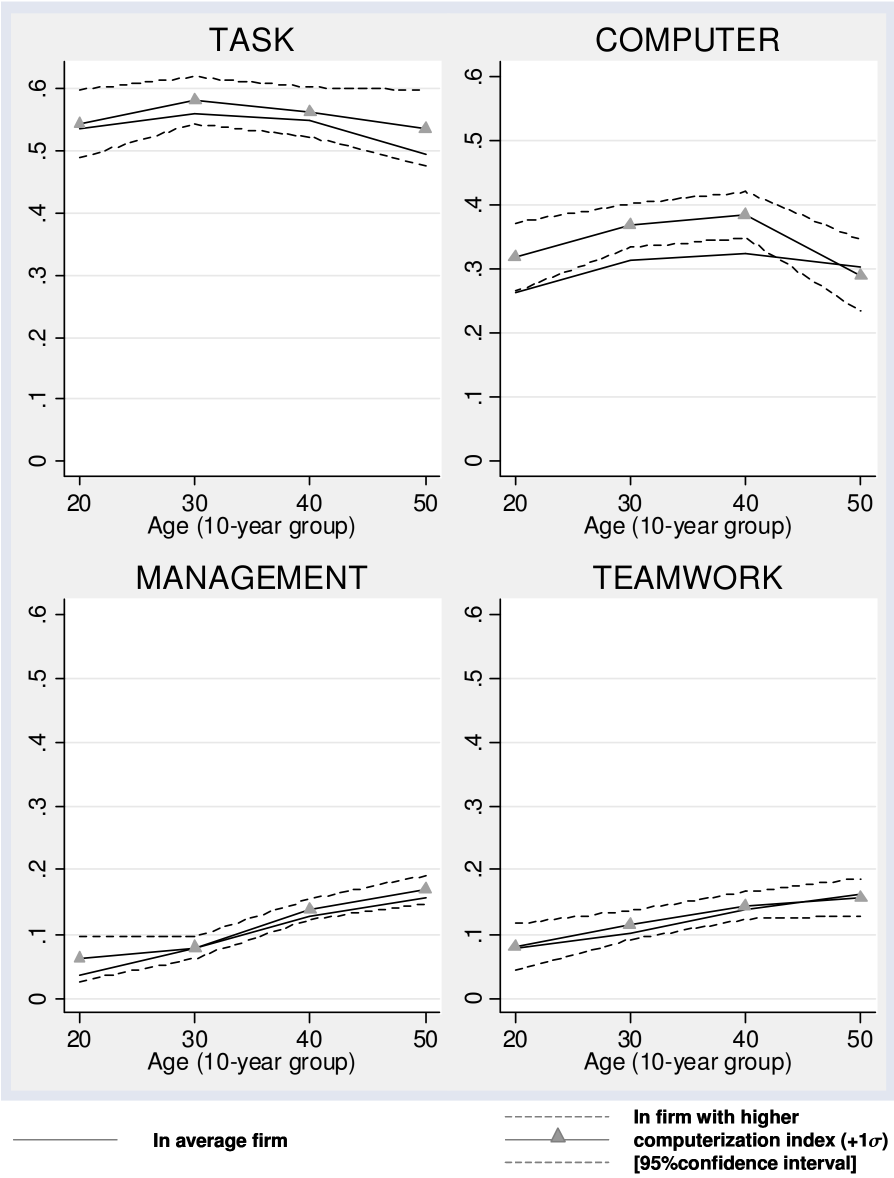

Figure 4: Impact of the computerization index on the incidence of four types of training

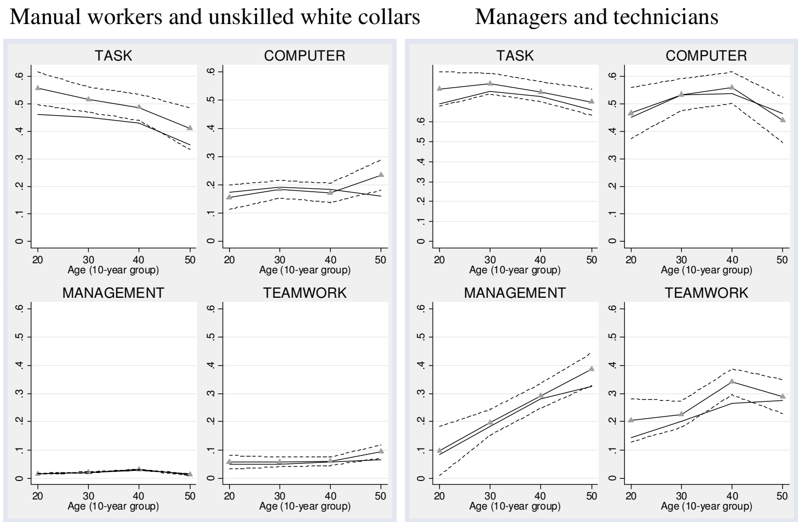

Figure 5: Impact of the organization index on the incidence of four types of training, by occupation

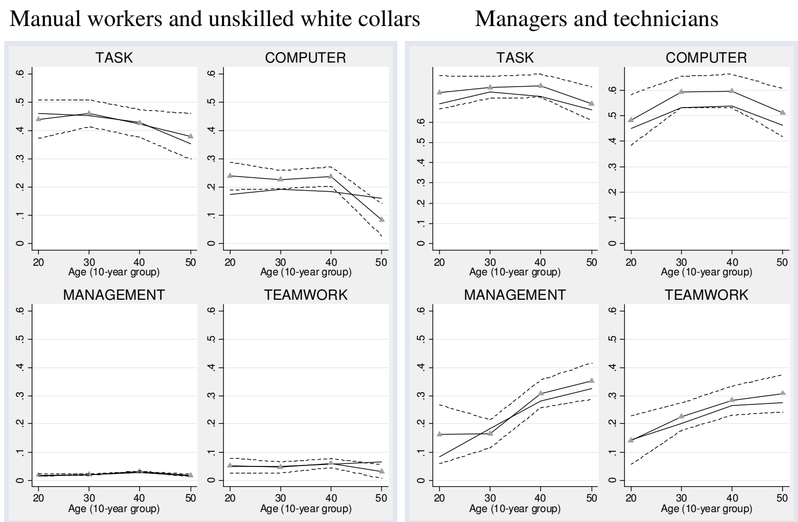

Figure 6: Impact of the computerization index on the incidence of four types of training, by occupation

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		

Figure 7: COI survey: questions on the firm's computerization

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 projects 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	

Figure 8: COI survey: questions on the firm's organization